Telfer School of Management

Faculty of Graduate and Postgraduate Studies

A Simulation Approach for Capacity Planning in an Open Community Care Network

Thesis submitted to the
Faculty of Graduate and Postdoctoral Studies
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For the MSc degree in Health Systems

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Abstract

One of the impacts of rising demand for community health services is on long term capacity planning. Demand for community services arises directly from the community-mainly seniors- as well as from those discharged from the hospital. This thesis is focused on developing a simulation model based on patient flow in a set of community care facilities in order to help reduce the back log of patients remaining in acute care due to a lack of capacity in these facilities.

Our model will provide the user with policy recommendations that address capacity allocation in different post-acute care alternatives over a multi-year time-horizon. In the model, patients differentiated by age and gender flow through the system with stochastic lengths of stay at each node (representing a facility type). We used historical data to classify patients. Proposed factors that influence the arrival and LOS parameters such as age and gender are tested on available data. We used Excel, Minitab and ARENA Input Analyzer to estimate the distribution of LOS, the arrival pattern and the age and gender distribution of new patients. We used Arena software for the simulation. The objective is to minimize patients waiting in the system subject to a constraint on the rate of expansion of facilities. Scenarios are informed by a previous queuing network model that provides the ideal capacity plan. The proposed method seeks to provide a means of determining the potential impact of various rates of expansion and changes in demand in order to more adequately plan future development.

Acknowledgment:

I would like to express my sincere gratitude to my supervisor, Professor Patrick, who really helped me through this learning phase of my academic life. I could not succeed without his support and valuable insights. His extraordinary support and encouragement will never be forgotten.

I would like to thank Jamie Stevens and Bruce Libman from CCAC and Champlain LHIN to provide us necessary data and their contribution in the phase of data analyses and coding.

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Contents

List of Figures

List of Tables

Introduction:

While aging is inevitable, Canada has never experienced such a significant aging in the population as it is currently undergoing. In 2015, seniors accounted for almost 15% of the Canadian population. For the first time in 2016, they will account for a larger share of the population than children aged 0-14 [7].

Figure 1 shows how the senior's population in Canada is increasing.

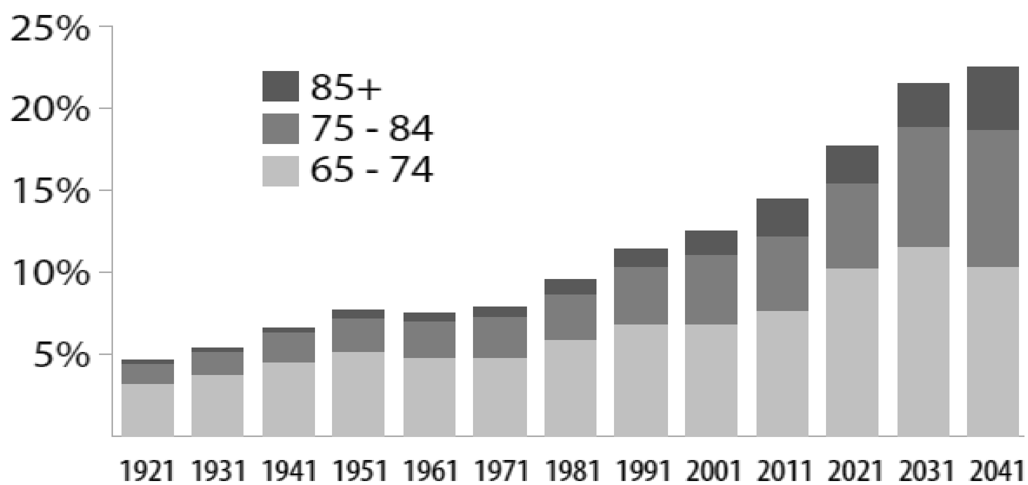

Figure 1. Seniors by Age Group, as % of The Total Population, Canada, 1921-2041[1]

Throughout the Champlain region, the senior population is projected to grow almost 10 times faster than the under-65 population. They will represent 16% of the population in 2016, and 25% by 2036[1]. Older Ontarians are a vital part of society. They are our grandparents, uncles and aunts, teachers and friends and are valuable because they have experience, expertise and wisdom. Seniors stay in emergency departments and acute care more frequently and for longer periods due to the additional assistance they may require after acute care [5]. So assessing the

[1] Champlain LHIN Overview,2014

health care needs of this precious part of the society and the resulting demand for health services needs to be emphasized.

In Ontario health care provision is divided into 14 geographical LHINs. They authorize 150 public hospitals over a total of 227 sites. In the last five years, more than 1 million patients have been discharged annually from these hospitals. Although most patients return home when they no longer require care in the hospital, over 20% of patients still require various levels of support. Such support includes home care (for example, nursing and personal-care services such as bathing provided in the patient's home) as well as specialized services provided by rehabilitation and ongoing care provided in either long-term-care homes or complex continuing care (CC) facilities.

Figure 2 shows the discharge destinations of hospitalised patients in Ontario in 2009[2].

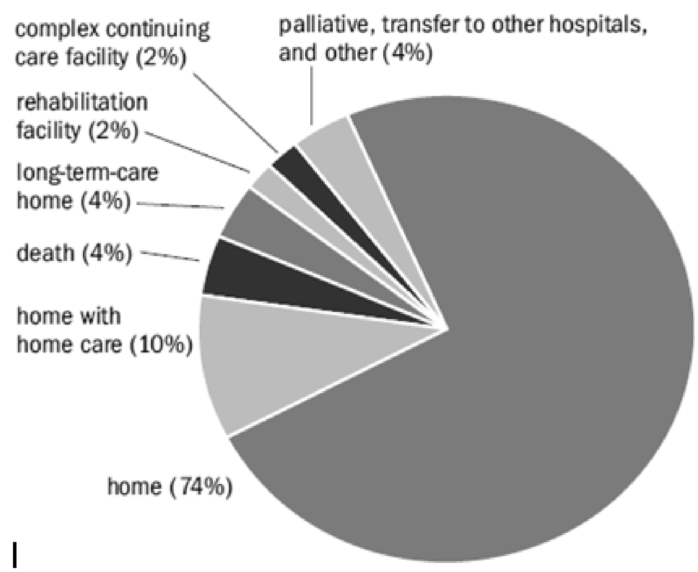

Figure 2. Discharge Destination of Hospitalized Patients in Ontario, 2009(%) [2]

It is important that the transition from hospital to home, or to another health-care setting, is done as soon as possible after the decision is made that the patient no longer requires hospital care. Remaining in hospital longer than medically necessary can be detrimental to a patient's health for various reasons including the risk of getting a hospital-acquired infection and, especially for older patients, a decline in physical and mental abilities due to a lack of activity. Further, waiting in hospital for a bed in a community setting or for other community based services including long term care and home care is much more expensive than the community-based care alternatives [3].

Finally, a shortage of in-patient beds can create problems throughout a hospital. For example, emergency patients may have to wait in the emergency department for a bed, post-operative patients may have to remain in the recovery room, and patients with pre-scheduled surgeries may have their surgeries cancelled [4]. Thus, from a quality of care perspective, a cost efficiency perspective or a managerial perspective, it makes little sense to have patients' discharge time delayed due to a lack of resources downstream.

Patients who are ready to be discharged but need to wait in the hospital for post-discharge care to become available (such as home-care services or placement in a long-term-care home, a complex continuing care facility, or a rehabilitation facility) are referred to as alternate-level-of-care (ALC) patients. In 2009, over 50,000 patients waited in hospital due to delays in arranging post-discharge care accounting for 16% of total patient days in all Ontario hospitals. LHIN-wide, an average of between 3% (Central West) to 21% (North East) of hospital beds are occupied by ALC patients[2]. In addition, the total days ALC patients were hospitalized increased by 75% between 2005/06 and 2009/10, while total hospital patient days increased by only 7% [3].

[2] Long-Term care fact sheet, May 2013

Thus, the ALC challenge is a significant and growing challenge to health care administration in Ontario and elsewhere.

The Discharge Process

During patients' stay in hospital, they are assessed on an ongoing basis by a multi-disciplinary team consisting of physicians, nurses, social workers, dieticians, etc. The team assesses the post-discharge placement as well as the estimated date of discharge. For example if a patient needs long term care or home care, the hospital contacts the Community Care Access Center (CCAC). The CCAC is responsible for assessing the eligibility of patients and arranging the right service for each patient. Any change in the patient's condition may impact the discharge date and the post-discharge destination.

When a patient no longer requires hospital care, the physician writes a discharge order. Under the Public Hospital Act the patient should leave the hospital within 24 hours. However, ALC patients may stay in the hospital longer due to the need for and the current lack of post-discharge care [3]. The rate of ALC days as a percentage of total hospital days has been described as an important indicator of health system performance [4].

Figure 3 demonstrates the ALC discharge destinations in Ontario in 2009.

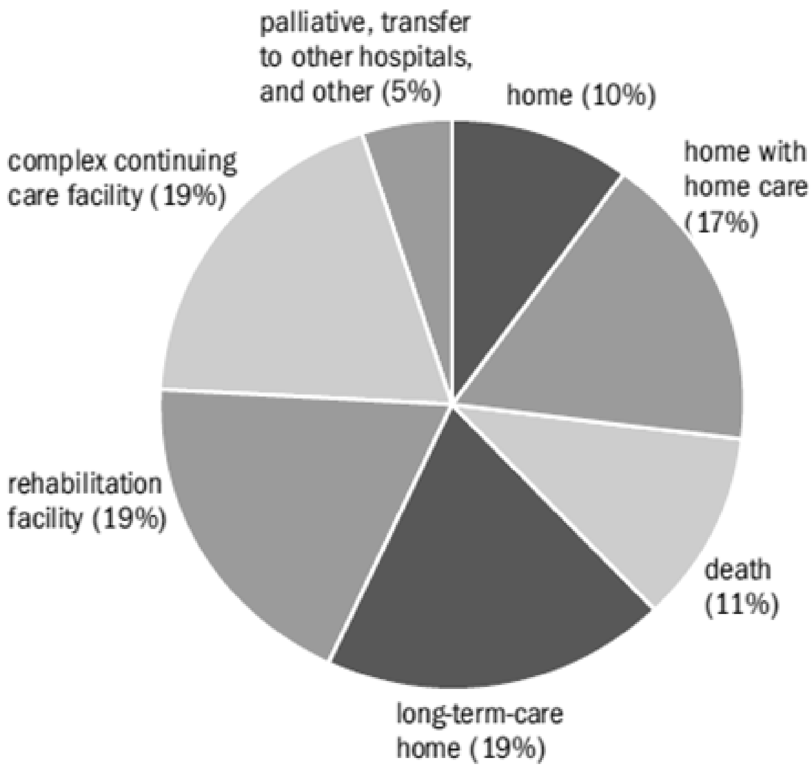

Figure 3. Discharge destination of ALC Patients in Ontario, 2009 [3]

According to Figure 3, upon leaving hospital, 19% of Canadian patients designated ALC are transferred to LTC homes, another 19% go to inpatient rehabilitation, 10% are discharged home with or without home care services, and 11% pass away during their ALC wait.

Statistics Canada reported that between 2003/4 and 2009/10 the total number of residents in a range of LTC facilities increased from 76,866 to 84,873 in Ontario. That is an increase of 8,007 residents, or 10.4%. The number of beds is increasing more slowly, growing by 7,186 beds from 81,849 beds to 89,035. That is an 8.8% increase. The population 85 and over is growing roughly four times more rapidly than the number of LTC beds. So, assuming a proportional relationship between the over 85 population and LTC demand, it is clear that the current capacity expansion in LTC beds cannot meet the increasing demand[3].

The latest report by Access to Care for the Ontario Hospital Association provides the provincial number of ALC patients occupying acute beds by discharge destination as shown in Table 1. This table confirms the necessity to efficiently plan capacity for these facilities. LTC and Home Care are the two main congested services having 30% and 18% of ALC patients on the waitlist.

Table 1. Number of ALC Patients occupying acute Beds by Discharge Destination as of Mach 31, 2015

Discharge Destination	Number of ALC Patients on the Waitlist	% of ALC Patients on the Waitlist
Long Term Care	782	30.3%
Home with CCAC Services	467	18.1%
Rehabilitation	332	12.9%
Complex Continuing Care	278	10.8%
Assisted Living	213	8.3%
To be Determined	186	7.2%
Palliative Care[4]	124	4.8%
Convalescent Care	115	4.5%

[3] Long-Term care fact sheet, May 2013

[4] Palliative Care Bed: Provision of medical or comfort care to support end-of-life planning to reduce the severity of a disease or slow its progress. The focus is on quality of life measures rather than providing a cure.[6]

Home with Services	39	1.5%
Home without Services	27	1%
Mental Health	15	0.6%

While the Ontario Ministry of Health and Long-term Care has suggested that new long-term care beds make up for hospital bed cuts, they do not even make up for the growth in the relevant population. Accordingly, wait times for LTC beds have more than doubled in recent years. Given the modest plans to expand the number of LTC beds, the situation may well get worse.

Community Care Network

A conceptual model of the post-acute care facilities will help in modeling the current situation and plan for future demand. Figure 4, which is based on the research done in this area by Noghani et al [6], depicts interactions among a number of different ALC destinations. He labelled it the community care network (CCN[5]). While there are other discharge destinations, it is clear from Table 1 that these are the main ones.

[5] CCN is an open queuing network with blocking in which each node represents one possible destination facility [6].

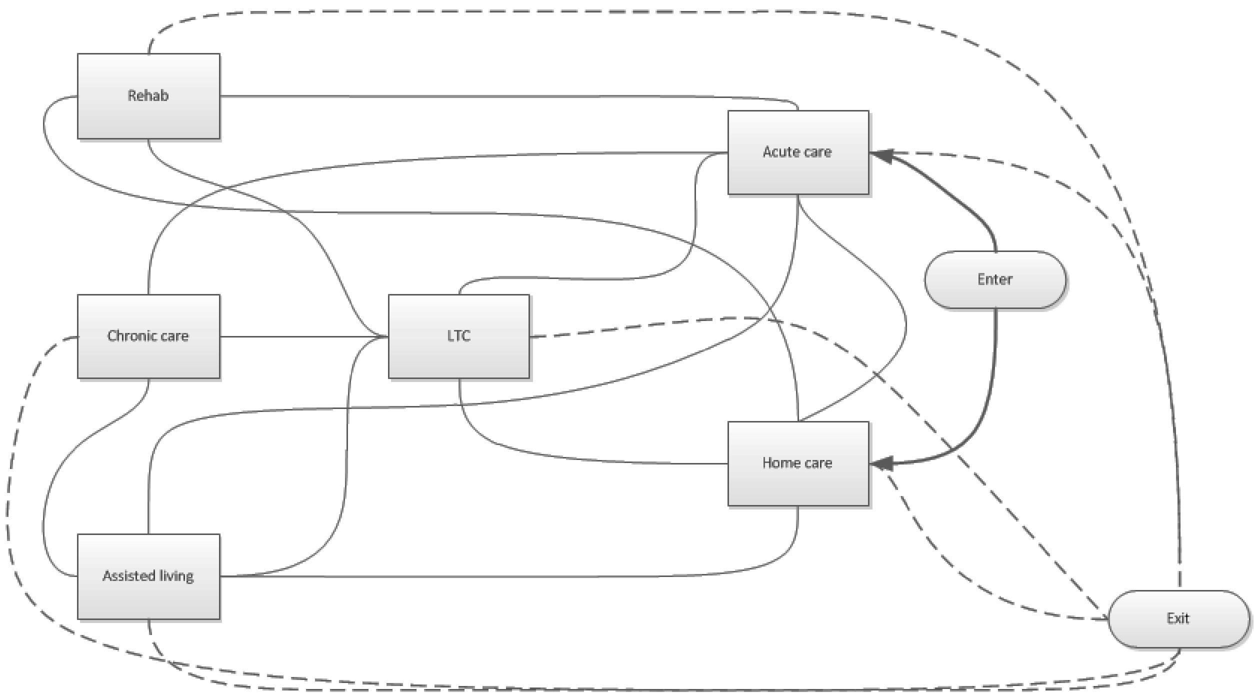

Figure 4. Community Care Network

The services and interactions shown in Figure 4 are the nodes and edges of the network. Edges represent the flow of patients between different nodes of the community care network. As shown, there are six possible ALC destinations: Long Term Care (LTC), Assisted Living, Rehab, Home Care, Chronic Care and Acute Care. Long Term Care (LTC) beds provide care to meet both the medical and non-medical needs of people with chronic illnesses or disabilities who require care that is not available in the community. The Assisted Living node provides care for patients who are able to mobilize independently but who may require assistance with activities of daily living [6]. Rehabilitation service aims to stabilize or improve health to the fullest extent possible and to help the patient adjust to daily life. Home Care services provide care in home, at school or in the community[6]. Services include professional healthcare like nursing, physiotherapy, occupational, speech language therapy and social work, personal care like dressing, eating and

[6] Government of Ontario

washing, home making services such as shopping and banking and end of life care. Chronic care or Complex Continuing Care[7] helps patients with chronic conditions like diabetes to recover their strength and mobility and return to the community. CC is provided in hospital for those patients that need technology based care that cannot be done in home. Acute Care provides necessary treatment for a disease or severe episode of illness for a short period of time with the goal of discharging patients as soon as they are stable[8].

It is important to consider post-acute care destinations as a network because demand for each node is dependent on the available capacity at other nodes due to the potential impact of blocked patients. Therefore isolating one node and putting it under scrutiny may result in unrealistic conclusions. As illustrated in Figure 4, the demand for facilities comes from both the community and the hospitals causing competition and increased wait times. Thus the health authority needs to balance the competing goals of keeping ALC patients under a reasonable threshold as well as maintaining wait times in the community for the same services at a reasonable level.

Research Objective:

While current long term care capacity expansion is not keeping pace with increases in the seniors' population [10], many Local Health Integration Networks are now working on ALC resource matching. This work aims to reduce the waiting times by improving patient flow between the hospital and community services with the goal of determining the impact of changes in capacity at each type of service on waiting times at all nodes [3].

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[7] Ministry of health and long term care, Ontario
[8] Canadian Institution for Health Information (CIHI)

In this research we seek to bridge the gap between community and hospital care by determining the necessary capacity (beds) that will meet the increasing demand of mostly seniors in the community as well as those attempting to access the community care network from acute care. This is complicated by the fact that there are multiple classes of patients competing for the same pool of resources who move through the network in a stochastic fashion. Further, the capacity plan needs to take into account potential increases in demand over a multi-year horizon.

Therefore the research question we seek to answer is:

"How do we incorporate a year-by-year capacity plan (number of beds) over a multi-year planning horizon for different facilities in an open community care network while accounting for the impact of age and gender on LOS and flow probabilities as well as potential increases in demand with the end goal of minimizing the number of patients waiting for service?"

Literature Review:

Attention to community based care is increasing, as policy makers become more concerned with allocating scarce resources efficiently and effectively [8]. Therefore, modeling patient flow between health services has received significant attention in the literature.

This thesis is the continuation of a line of recent research on patient flow in a network of care. Patrick (2011) provided a Markov Decision process model to determine the optimal policy for placement of hospital patients into LTC so as to keep the number of patients waiting below a pre-determined threshold [12]. While the MDP policy presents a solution to the congestion in the hospitals by ensuring a predictable and manageable census of ALC patients in the region, Patrick demonstrated that without increased capacity, the wait times for clients attempting to access LTC directly from the community are well above the 90 day target. The paper deals solely with the needed access for hospitals to LTC in order to prevent congestion in the hospital but does not quantify the potential impact on those seeking access to LTC directly from the community.

In 2015, Patrick et al. [10], used simulation in order to model patient flow out of both hospitals and the community to LTC facilities and assisted living homes. Demand is differentiated by location, facility preferences, accommodation type requirement (private or ward bed), priority and eligibility for assisted living. In this paper, they used the MDP model from Patrick (2011) in order to find a “trigger value” as an input to the simulation. The trigger value is the threshold such that once the number of patients awaiting placement in the hospital exceeds it, the hospital receives priority access to available LTC beds. Patrick demonstrated that without increased capacity (in AL) and reduced LOS (in LTC) the wait time target of 90 days for community demand cannot be reached.

While Patrick et al.[10] used simulation to determine the impact on community demand and explored the necessary increases in capacity and reductions in LOS in order to meet performance targets, the simulation does not address the issue of how the reduction in LOS is to be achieved. Since the only way to reduce LOS in LTC is to provide greater home care and AL in order to delay entry to LTC, it is important to determine how much extra capacity is needed in those nodes. Noghani et al. (2014) attempted to answer this question by developing a queueing network model that predicts the extent of backlogs that can be expected in the network of care illustrated in Figure XX for a given capacity plan for each node. To do this, they made us of queuing network models that incorporate blocking currently in the literature. (Blocking refers to the scenario where a patient is ready for discharge but has to be held at a given location due to the lack of an available in the destination facility.) Thus, before outling Noghani's work we first describe the two most relevant queuing network models in the literature.

Koizumi et al. used a queuing model with blocking to analyze the flow of patients out of acute care and into a series of mental health facilities. They used a multi-server model to present both mathematical and simulation results. Their system consists of three types of Psychiatric institutions that patients visit in sequence. The accommodations outside their system are categorized into two groups – acute care and community. The network is illustrated in Figure 5.

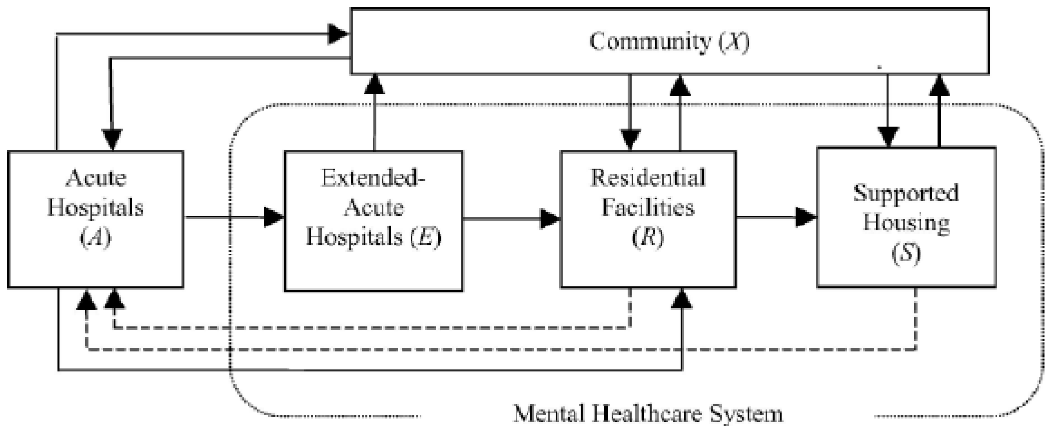


Figure 5. In flow and Out flow of Patients in Koizumi et al.'s model [11]

Dotted lines represent insignificant patient flows that were omitted in the model. The authors assumed a single first-come-first-served queue for all patients arriving at any given station. Performance measures were the number of patients waiting to enter each facility and the associated waiting time. In addition simulation was used to analyze short term transient performance and test the robustness of the mathematical model [11]. Tellingly, the model suggested that an increase in supported housing beds would reduce the stress on the higher intensity services.

Building on the work of Koizumi et al, Bretthauer et al. presented a new heuristic method for tandem systems with blocking. They use a queuing network system to model patient flow between intensive care units (ICU), step-down (SD), acute care (AC), and post-acute care units (PAC) in a large hospital located in the United States. They developed a method to determine the optimal combination of beds at different units that minimizes a weighted sum of blocking probabilities for a given set of resources. They determined a “good” (meaning low cost) capacity plan while ensuring a specified level of service quality by simulating a large number of potential capacity plans over a fixed time horizon [14].

Noghani et al (2014) built their model as an extension for the simulation model of Patrick (2015) to incorporate the whole CCN. Their model was built based on Bretthauer's approximation model (2011) in order to estimate blocking probabilities for the nodes of the community care network [6]. Since there are a large number of servers (beds) and flow is not tandem, some modifications to the formulas in Bretthauer's algorithm were required. The numbers of waiting customers at each facility as well as the blocking probability at each facility were estimated. Noghani et al. used recursive functions in order to avoid computationally intractable powers of number of beds in order to estimate waiting time and blocking probability. The model is shown to provide reasonable estimation of long run average wait times and the blocking probabilities, provided that the demand is limited to be less than the effective service rate in order for the model to be stable but it remains a predictive model with no optimization.

To rectify this, Bidhandi et al. (personal communication), used simulated annealing as a means of determining the minimal cost capacity plan subject to a upper bound on the sum of the blocking probability over all facilities. In the first stage, a forward SA algorithm has been proposed to find the best initial feasible solution. In the second stage, a backward SA algorithm has been utilized, where the initial solution is improved iteratively.

Through the papers outlined above, a queuing network model has been developed combined with an optimization model that provides a minimum cost capacity plan based on a fixed demand stream and assuming the system reaches steady state. However, there remain limitations associated with the work to date. None of the aforementioned research provide a year by year capacity plan that details the impact of transitioning from the current state to the steady state capacity plan. In addition, the queuing network model assumes a homogeneous set of patients whereas research has shown that both patient flow and LOS are impacted by a number of characteristics including age and gender. It is unknown, based on the literature above, whether the simplifying assumptions required by the queuing network model would undermine the results.

In this paper we filled this gap by focusing on a methodology that allows us to examine transient behaviour as capacity is added to the system of a multi-year planning horizon and that is flexible enough to allow us to provide a more realistic setting where patients are differentiated appropriately. We will illustrate how the performance of the steady state capacity plan can be affected in the more realistic setting of differentiated patient cohorts and potentially changing demand. In addition, we look to incorporate into the analysis forecasted changes to demand rather than relying on the simplifying assumption of a steady demand rate.

In order to incorporate transient behaviour associated with varying capacity and demand, we turn to simulation as the methodology of choice. Simulation has been shown to be a popular method for evaluating the operations of a health care facility under predefined resource capacity levels. Harper and Shahani argue that reducing the complexity of a problem to make more analytical solution methods tractable is less than ideal [9]. Discrete event simulation is an operational research technique that enables the end-user to assess the existing heath system and do sensitivity analysis around uncertain or changing parameters. Unlike analytical methods, simulation is not an optimization tool. It can provide performance measures for various policies

[16]. Moreover, simulation as a tool for non-math end users in health settings is more transparent and easier to communicate.

In a paper by Bozena Mielzarek et al. [17], a survey of the literature was conducted to determine the health care areas supported by simulation models. Statistics in his paper show Discrete Event Simulation (DES) was used 118 times which is 75.64% of published simulation models. 26 of these 118 published models were with the application of epidemiology, health promotion and health policy, 76 with the application of health care systems operations and 8 for health and system design. The advantage of DES stems from its flexibility, its ability to handle variability, uncertainty and complexity, and the option of performing 'What if' analysis.

As an example, Peter Van Berkel et al. used simulation in order to model the flow of elective and non-elective general surgery patients through the operating room to the recovery beds. The simulation accesses a central data base that stores all the model parameters. Non-simulation experts can thus input the model parameters and run the model themselves. They analyzed different options to improve the use of current resources. The analysis examined the consequences of redistributing beds between sites and achieving length of stay targets. The simulation showed long wait times are more dependent on beds rather than available OR time [18].

Zhang et al. developed a simulation model to determine optimal LTC capacity levels needed each year to satisfy a service level criterion based on a patient's wait time. Key elements of this approach include using demographic data (age and gender) and survival analysis to predict arrival and length of stay distributions for input into the simulation model. They used a simulation optimization approach in modeling the system as a multiple server (bed) queuing network with varying arrival and service rates (classifying patients) over a multiyear planning horizon [15].

Currently there is no simulation model of the community care network except the research by Patrick et al. (2015) that was limited to just three nodes including Acute Care, Long Term care and Assisted Living. He also did not consider multi-year planning in his research or patient demographics. Zhang et al.'s work includes year by year scheduling but it is limited to LTC. In addition, there is little research on capacity planning in community care that allows for patient flow and LOS to depend on patient characterisitics. This despite evidence that patient demand, flow and LOS are impacted by such characteristics as age and gender. In a paper by Hare et al. (2009), the authors demonstrate that gender, age, mental state, ethnicity and geographic location are all important factors in community care models. They developed a deterministic multi-state Markov prediction model to predict future demand for community based services including both privately and publicly funded LTC programs in British Columbia. They consider the predicted demographic changes and the relationship between age and health status in their model. However the focus was on predicting future demand rather than required capacity[13].

In this research we bridge the gap between community and hospital care by determining the necessary capacity (beds) that will meet the increasing demand of mostly seniors in the community as well as those attempting to access the community care network from acute care. We demonstrate the impact of age and gender on patient flow and LOS and develop a model that simulates the movement of heterogeneous patients within the community care netowrk, that allows for varying demand and capacity each year and that predicts changes to congestion levels for a given multi-year capacity plan.

In the following chapters, we first discuss the analysis of the data and describe in detail the setting of our model. Next we provide the model description and the required inputs. Finally, the model is validated and results and conclusion are provided.

Background and data:

The CCN parameters are obtained from three data sets from the Champlain Community Care Access Center (CCAC) and the Champlain LHIN. The Champlain LHIN is an organization that aims to help with the coordination of health services in order to ensure that services are well organized, appropriately funded and people will receive suitable care in a timely fashion. CCACs are local agencies that provide information as well as a link to local community support service agencies like home care, assisted living and LTC.

Datasets were analyzed in order to determine the required parameters for the simulation model. Parameters include the probability of flow between nodes as well as the average Length of Stay (LOS) and the arrival pattern. The current capacity of each node was provided by the LHIN. The following section provides descriptive statistics of the available data with added focus on the three primary nodes of Acute Care, Long Term care and Home Care.

LHIN dataset

The dataset from the LHIN includes records for Acute Care (AC), Long Term Care (LTC), Rehab (R) and Chronic Care (CC) patients. It contains records for each visit of each patient including their admit date and discharge date and the service facility as well as their post discharge destination. We used the CCAC data set for Home Care arrival, LOS and outflow analyses. Records include the Home Care (HC) patients' referral start date and end date as well as discharge destination and health status. Due to the unavailability of data for Assisted Living (AL), outflow probabilities and the mean LOS for this node is derived from previous research done by Noghani et al. [6]

Table 2 shows the number of available records from the two data sources.

Table 2. Summary on available data from CCAC and LHIN

Service type	Number of Records	Number of Patients
Acute Care	258663	163308
Chronic Care	3909	3909
Home Care	13533	104834
Long Term Care	19649	13394
Rehab	8094	8094

Acute Care:

Acute Care is one of the main entrances to the network. There are 258663 records for 163308 patients in three fiscal years (those discharged between 2013 and 2015). Among these patients, 69.1% have just one visit, 86.5% have two or fewer visits, 92.7% have three or fewer visits and 99.01% have 7 or fewer visits. Demand is mostly from the community with 92.69% of Acute Care demand arriving from home, then from LTC with 6.04% while referrals from other nodes in the CCN comprise less than 2% of AC demand. Figure 6 depicts a histogram of daily demand from the community from January 1st, 2013 through June 26th of 2015. Our data analyses showed there is a significant difference in number of admissions on weekdays as opposed to weekends. Therefore, arrivals are categorized based on day of the week and two separate probability distribution graphs have been made that represents Poisson distributions for weekend and weekday demand.

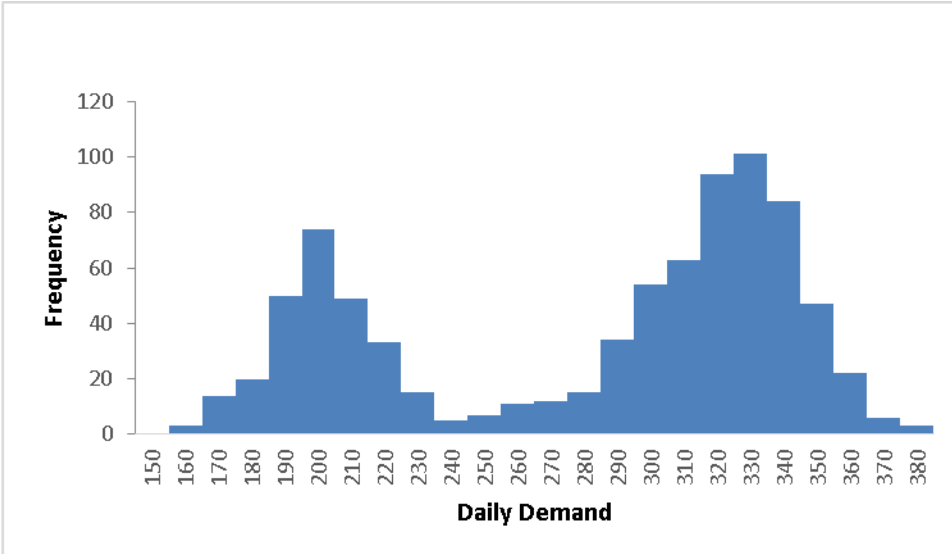


Figure 6. Probability Distribution of Acute Care's Demand in Weekends and weekdays

For more clarification, two separate probability distribution graphs for weekends and weekdays are presented in Figure 7 and Figure 8. The small initial hump in Figure 8 is likely due to statutory holidays.

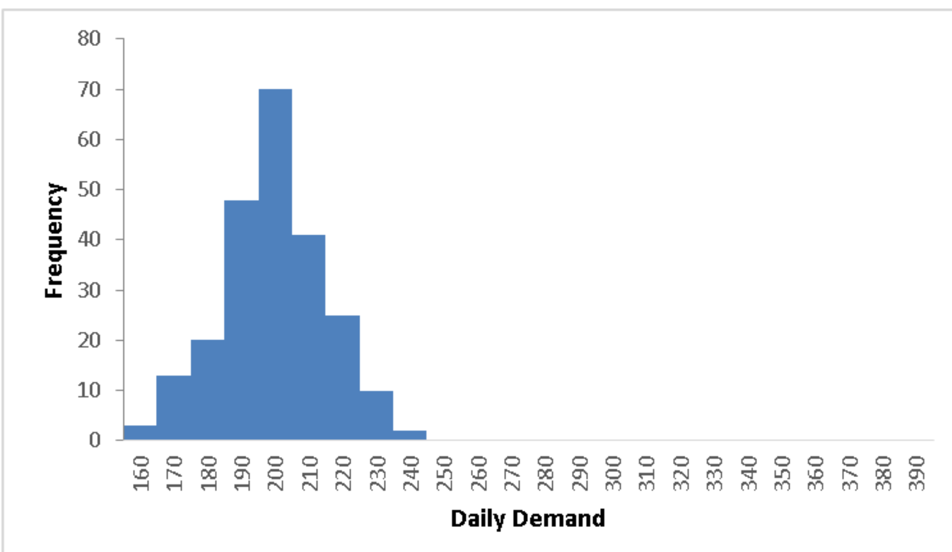


Figure 7. Probability Distribution of Acute Care's Demand in Weekends

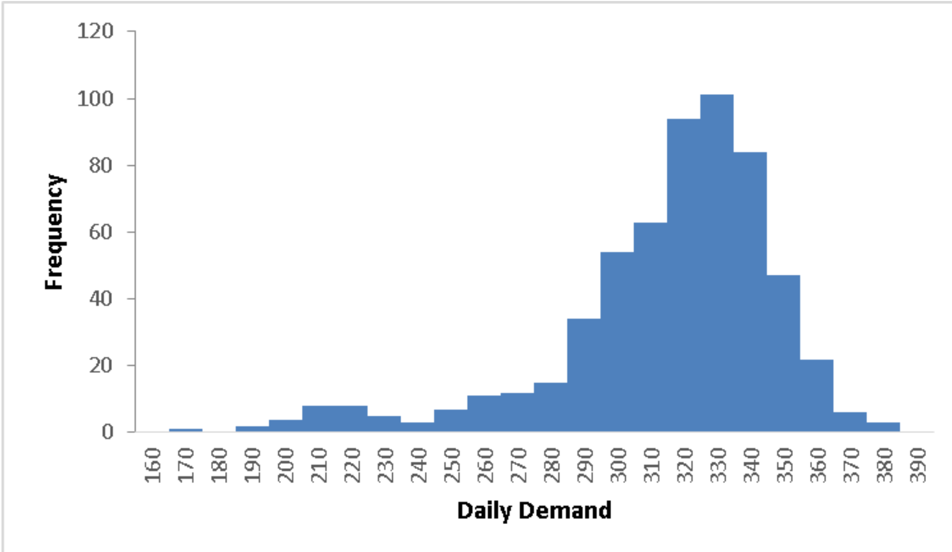


Figure 8. Probability Distribution of Acute Care's Demand in Weekdays

Year by year mean and standard deviation of the demand distribution are given in Table 3 demonstrating fairly stable demand:

Table 3. Acute Care Demand in Three Fiscal Years

Year\Descriptive Statistics (Per day)	Mean (Number of Arrivals)	STD	Max	Min
2013	267.75	60.51	363	156
2014	270.01	60.53	381	155
2015	270.75	58.71	374	169
Total	269.5	60.07	381	155

At each starting point, there are some patients who are in care from previous periods. The number of patients who are still in care is essential to our model because ignoring those who are in care at the start of the planning horizon may result in misleading output for capacity planning. On average there are 1890 patients in acute care at the start of the planning year. Figure 9 shows the average number in care for each month during these three years.

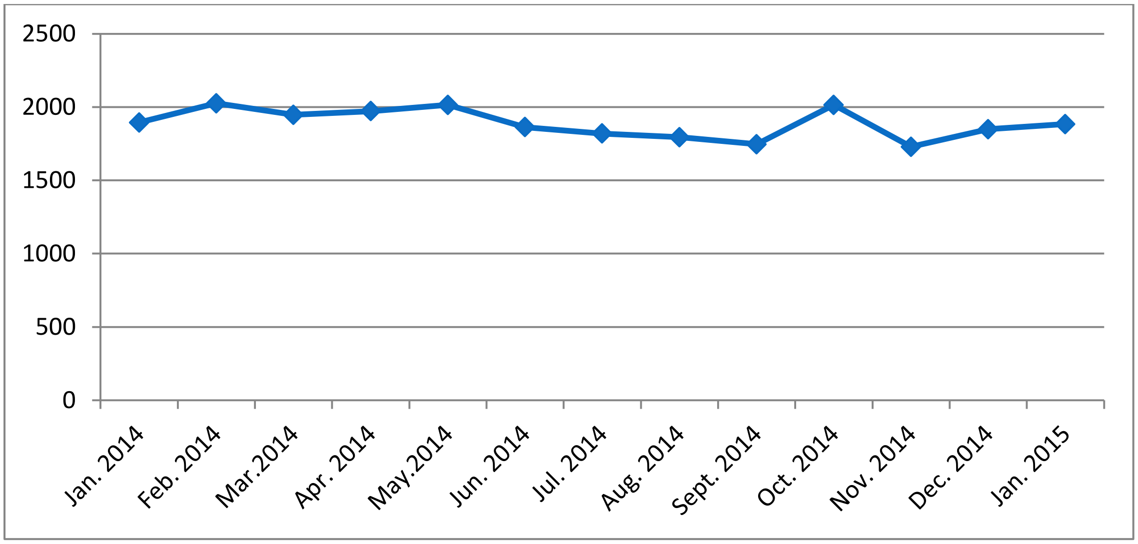


Figure 9. Acute Care Patients Who are Still in Care by the Start of Each Month

Although there is not a steady trend in the census, we use the simple average at the start of each month as input to the model.

Home Care:

Having 68.36% of its demand coming from the community, Home Care is a major entry point to the network. The format of records for Home Care is different from the LHIN data set. In this data set we have the referral source. So, when a patient goes to hospital and he or she qualifies as a Home Care patient, he/she will go to the waitlist and meanwhile, the patient may transfer to other nodes for a period of time until finding the right service from CCAC. Figure 10 and Figure 11 show the arrival pattern for weekends and weekdays.

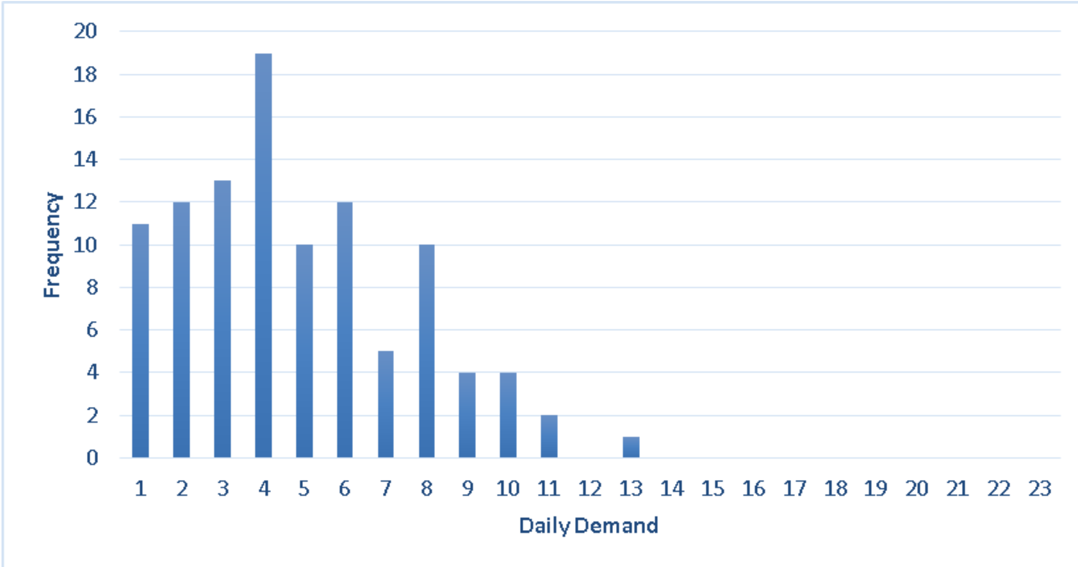


Figure 10. Probability Distribution of Home Care's Demand on Weekends

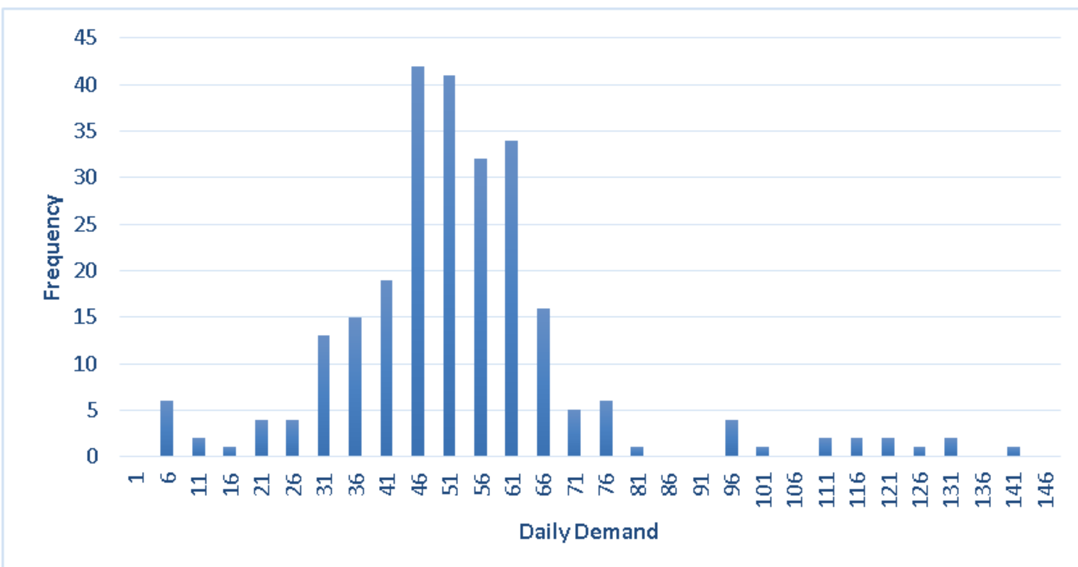


Figure 11. Probability Distribution of Home Care's Demand on Weekdays

Table 4 depicts demand statistics for years 2013 to 2015.

Table 4. Demand Statistics for Home Care

Year\Statistics (Per Day)	Mean (Number of Arrival)	STD	Min	Max
2013	44.25	23.75	1	165
2014	46.72	24.86	3	86
2015(Jan.-Mar.)	45.24	12.53	1	84
Total	45.4	19.00	1	165

In the Home care data set, there are 156877 records for 104834 patients. These records are for patients who received home care between 2009 and 2015. Home care patients are not monolithic. Rather they are divided into "population categories" based on the services they are receiving. Periodically, based on the patient's health status, the category of the patient will be updated. The list of categories and the proportion of patients in each one are provided in Table 5.

Table 5. Home Care Populations

Home Care Population	Adult Chronic	Community Independence	Adult Complex	Adult Short Stay	Other
Proportion	23.89%	15.23%	14.93%	30.93%	15.01%

Therefore, instead of having admit date and discharge date of the Home Care patient, there are "Home Care Population Start Date" and "Home care Population End Date" in the dataset that delineate changes in the services provided to that patient. There is a separate record for each patient in the Home Care data set accounting for population changes. LOS in Home Care is the sum of all LOS's in different populations for a patient. The census in Home Care, from April 2013 to March 2015 for the aforementioned populations is depicted in Figure 12. The significant drop in the population entitled "community" reflects a shift towards less complex patients being served elsewhere.

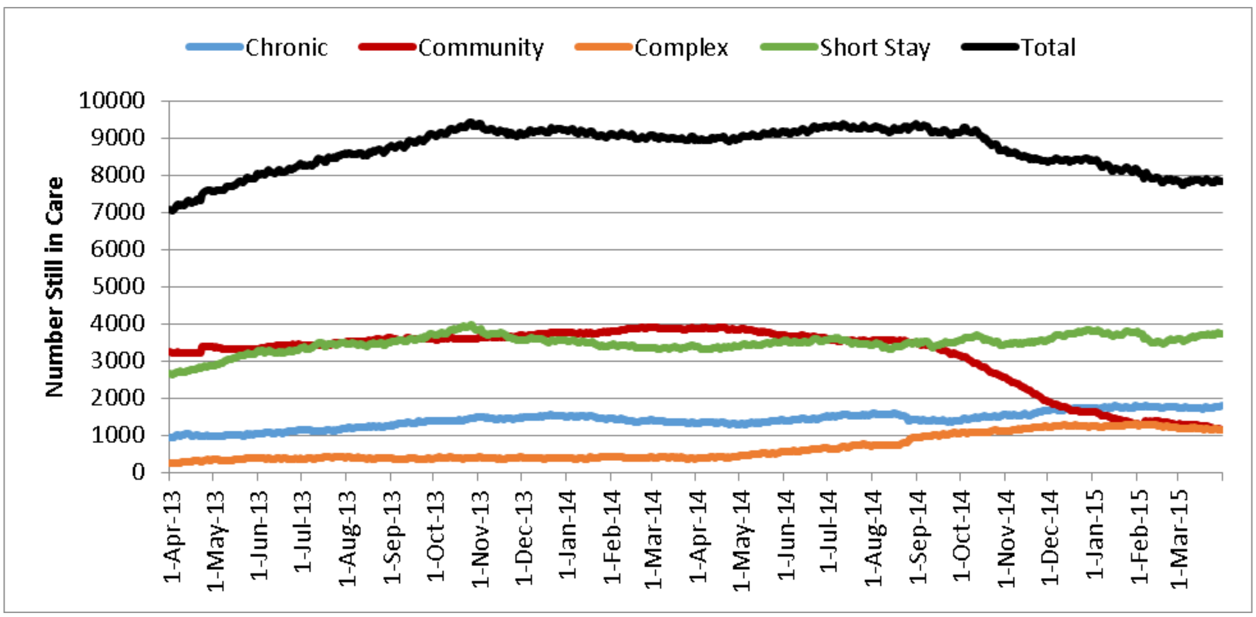


Figure 12. Initial Population in Home Care for the Four Main Populations

Long Term Care:

There are 19649 records for 13394 Long Term Care patients. 68.18% of patients have one visit, 88.06% have two or fewer visits, 94.40% have three or fewer visits and 99.03% of the population have eight or fewer visits. The data set contains information for patients who are discharged in years 2013 to (August 28th) 2015. This includes patients who were admitted many years ago (earliest entry year is 1965) but who were still in care at the beginning of 2013. Although 7041 records for 5015 patients have not been discharged yet which means statistically they are right censored, survival analyses of LOS demonstrates that it does not have a significant effect on the average LOS compared to the distribution of LOS for discharged patients (see Appendix XX). LOS analyses are based on records up to the eighth visit and are shown in Table 6 for three years (2013 to 2015).

Table 6. LOS in Long Term Care for Years 2013 to 2015

Year\Statistics	Mean(days)	STD	Min	Max
2013	542	898	1	16054
2014	504	891	1	18164
2015	551	886	1	13880
Total	534	892	1	18164

Demand for Long Term Care comes mainly from the hospital (59.17%). 25.93% of transfers are from the community, 5.57% of the LTC population were transferred from chronic care, 8.03% came from Home care and 1.3% of patients were transferred from Rehab.

Patients who are still in care by the start of each month during years 2014 and 2015 are depicted in Figure 13.

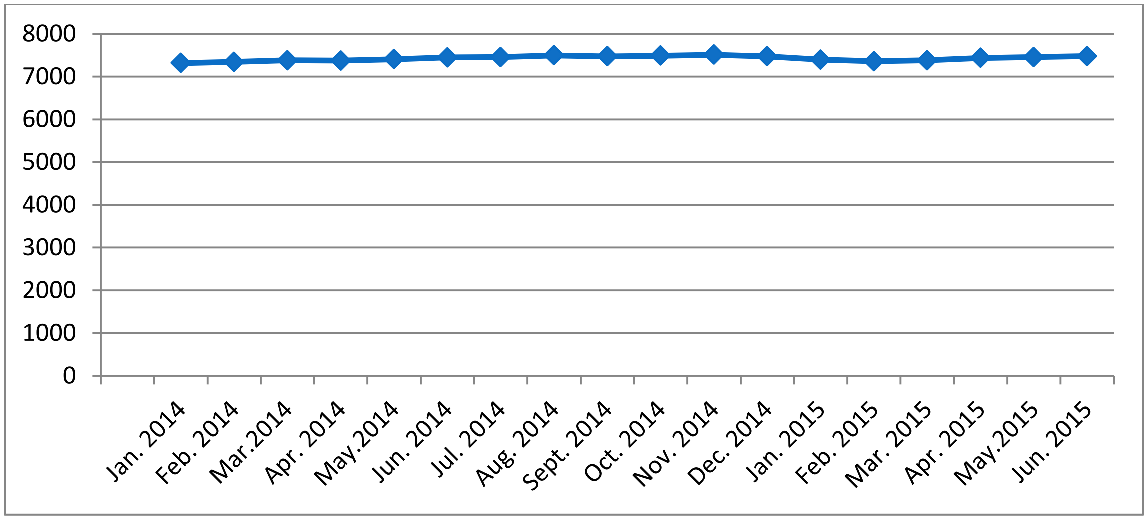


Figure 13. Number Still in Care in Years 2014 and 2015

The two main entry nodes to the system as well as Long Term Care which has long LOS and significant transfers in and out are discussed above. Required information for Chronic Care and Rehab as well as the other parameters of the model are elaborated below in the **CCN Parameters.**

CCN Parameters

In the following we discuss descriptive statistics of the CCN parameters that are used for the simulation inputs. LOS and flow probabilities are age-gender cohort dependant.

Initial Population

At the start of the planning horizon, January 2015, the number of beds is pre-filled. The number is the average number of those who are still in care and is depicted in Table 7.

Table 7. Average Number of Patients Still in Care for Each Node

Node	Acute Care	Chronic Care	Long Term Care	Rehab	Home Care	Assisted Living
Initial Population	1890	565	7041	233	10214	655

Demand

We considered two main entry nodes (AC and HC) as they are the only two with a significant inflow of patients coming from the community. Numerically, 92.69% of Acute Care and 68% of Home care are from the community. The average of number of arrivals per day is depicted in Table 3 and Table 4.

Patient Classes

Since past studies by Zhang et al. (2012) and Hare et al. (2009) and our own analysis have shown that people with different age and gender may have different arrival and LOS distributions, we classified patients into 12 groups based on age and gender. Age cohorts include Less than 50, 50-60, 60-70, 70-80, 80-90 and more than 90 and gender includes male and female patinets. The choice of 12 groups was based on a natural grouping of patients into 10 year cohorts. Under 50 were grouped together due to the smaller number of such patients in all nodes other than AC. Although there may be other potential factors like diagnosis or CMG+ that influence patient behaviour, we chose to use age and gender as the strongest factors and the ones most readily available from the data. Flow probabilities and LOS distributions were then determined for each age/gender cohort. Table 8 shows the discrete probability of having a specific class for each node.

Table 8. Discrete Probability of Being in a Patient Class

Gender	Female						Male					
Age Cohort	0-50	50-60	60-70	70-80	80-90	>90	0-50	50-60	60-70	70-80	80-90	>90
AC	29.31 %	4.98 %	6.43 %	6.89 %	7.09 %	2.95 %	14.76 %	5.51 %	7.46 %	7.37 %	5.81 %	1.44 %

CC	2.78 %	4.22 %	9.01 %	11.91 %	18.25 %	7.84 %	2.90 %	4.82 %	8.50 %	12.39 %	13.94 %	3.44 %
LTC	1.28	2.08	4.77	11.20	25.56	15.52	0.98	2.29	4.75	8.99	16.46	6.12
HC	7.37 %	5.24 %	7.56 %	10.70 %	16.81 %	8.60 %	7.57 %	5.05 %	7.44 %	9.25 %	10.87 %	3.54 %
R	2.42 %	4.04 %	7.73 %	13.94 %	21.87 %	9.27 %	2.79 %	4.32 %	6.89 %	10.15 %	13.08 %	3.49 %

Initial patients in each facility are assigned probabilistically to each class based on the discrete probability distribution in Table 8.

Flow probabilities

According to our analyses, the total non-classified routing probabilities out of each node in the CCN are shown in Figure 14. The numbers surrounding each node represent the outflow probabilities from that node as derived from the data.

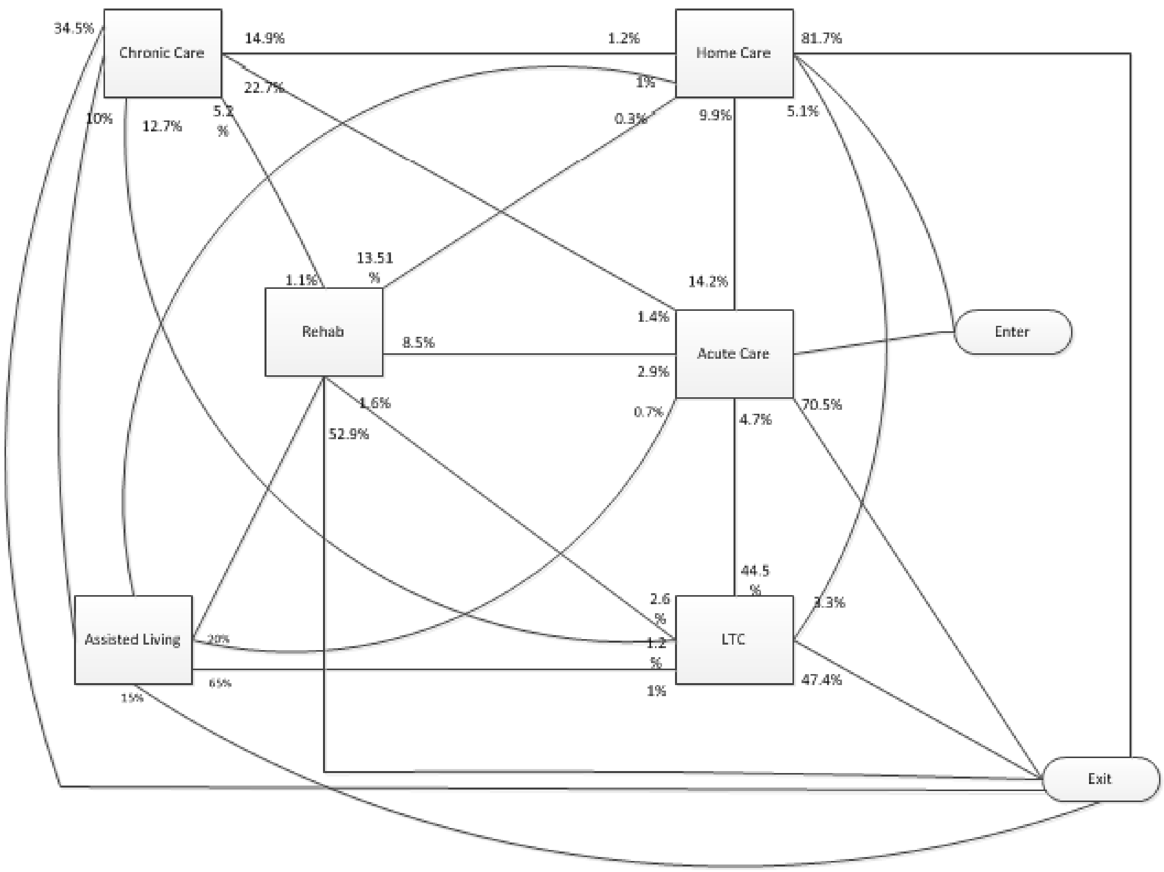


Figure 14. CCN outflow probabilities

As mentioned earlier, we used outflow probabilities for Assisted Living derived from previous research. According to Noghani et al. [6], 65% of Assisted Living patients transfer to Long Term Care, 20% transfer to Acute Care and 15% leave the network. As Figure 14 depicts, among those patients from hospital who remain in the network, most of them transfer to Home Care, then Assisted Living and then Long Term Care. Transfers from the other network entry point, Home

Care, is mainly to Acute care and LTC. Interestingly 45% of LTC patients will transfer to Acute Care. Many of these referrals are for a short period of time.

Figure 15 to Figure 24show the flow probabilities out of each node for different classes of patients. The node "OUT" refers to discharges out of the network either due to death or discharge home without services. Out flow in percentages are given in the Appendix.

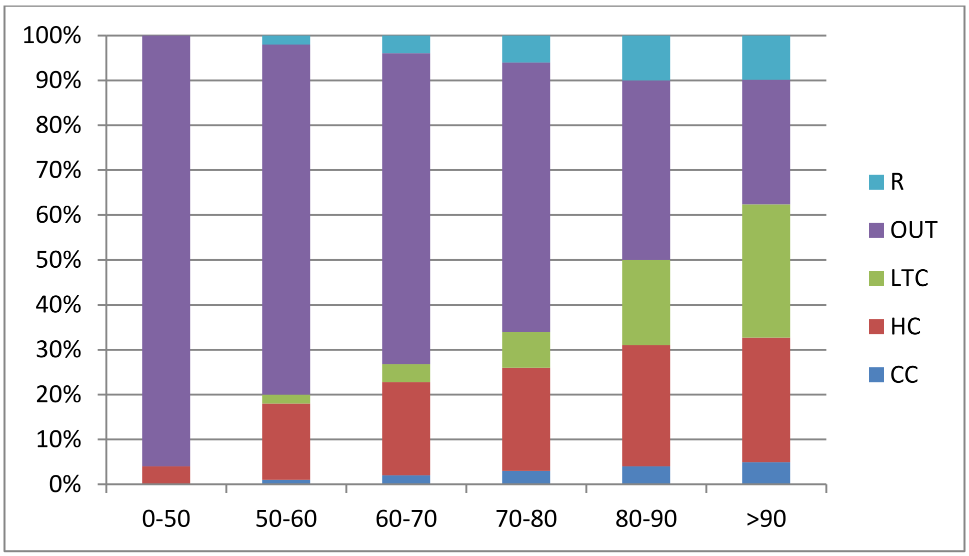


Figure 15. Flow probability Out of Acute Care to Other Nodes, Female Patients

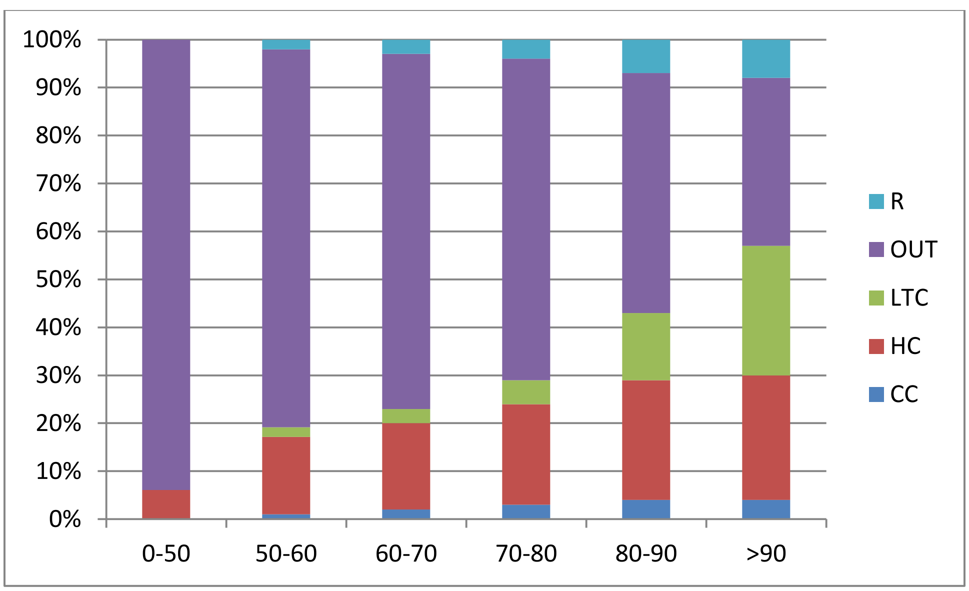


Figure 16. Flow probability Out of Acute Care to Other Nodes, Male Patients

As shown in Figure 15 and Figure 16, older patients from Acute Care are more likely to discharge to Home care and Long Term Care. Also the probability of being discharged out of the network is less for the older cohorts. We have mostly the same behaviour for both male and female patients.

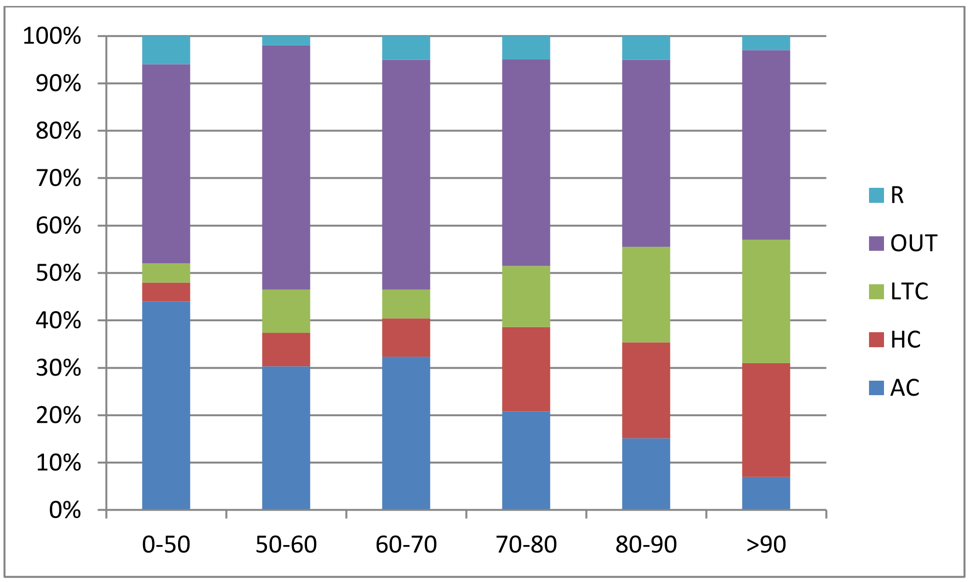


Figure 17. Flow Probability Out of Chronic Care to Other Nodes, Female Patients

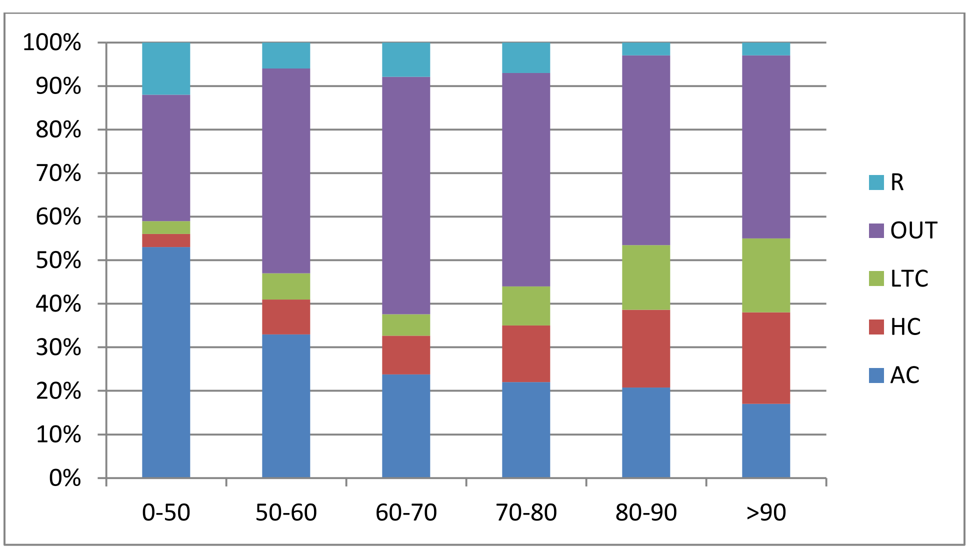


Figure 18. Flow Probability Out of Chronic Care to Other Nodes, Male Patients

Error! Reference source not found. and Figure 18 demonstrate that the probability of ransferring from Chronic Care to Acute care, Home Care and Long Term Care increases as admit age grows. The probability of exiting the network directly from Chronic Care decreases for older age cohorts.

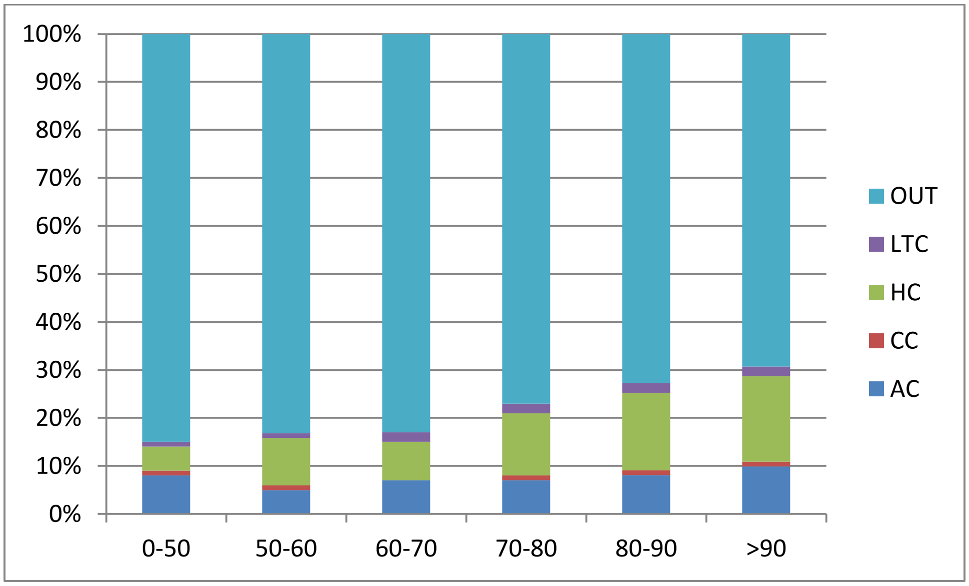


Figure 19. Flow Probability Out of Rehab to Other Nodes, Female Patients

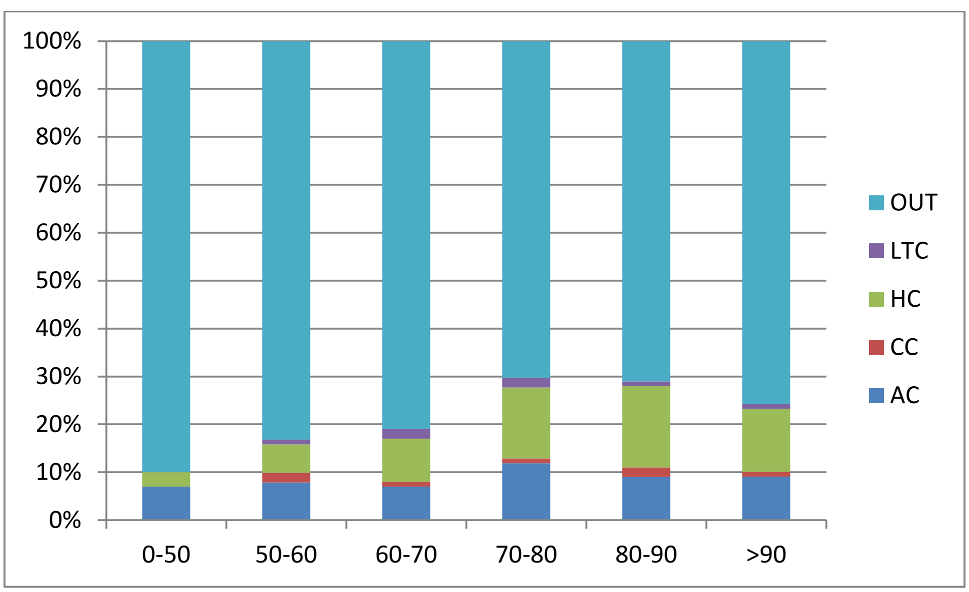


Figure 20. Flow Probability Out of Rehab to Other Nodes, Male Patients

In Rehab, patient behaviour in terms of outflow is the same for both female and male patients. While the probability of transfers to other nodes remains relatively consistent for different age groups, those in the older cohorts tend to stay in the system for longer periods and transfer to Home Care more frequently.

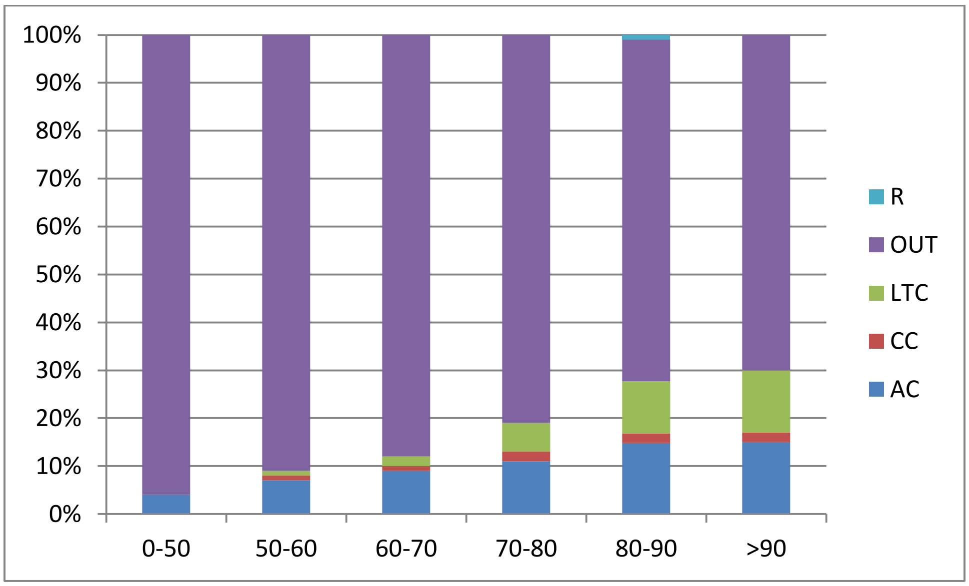


Figure 21. Flow Probability Out of Home Care to Other Nodes, Female Patients

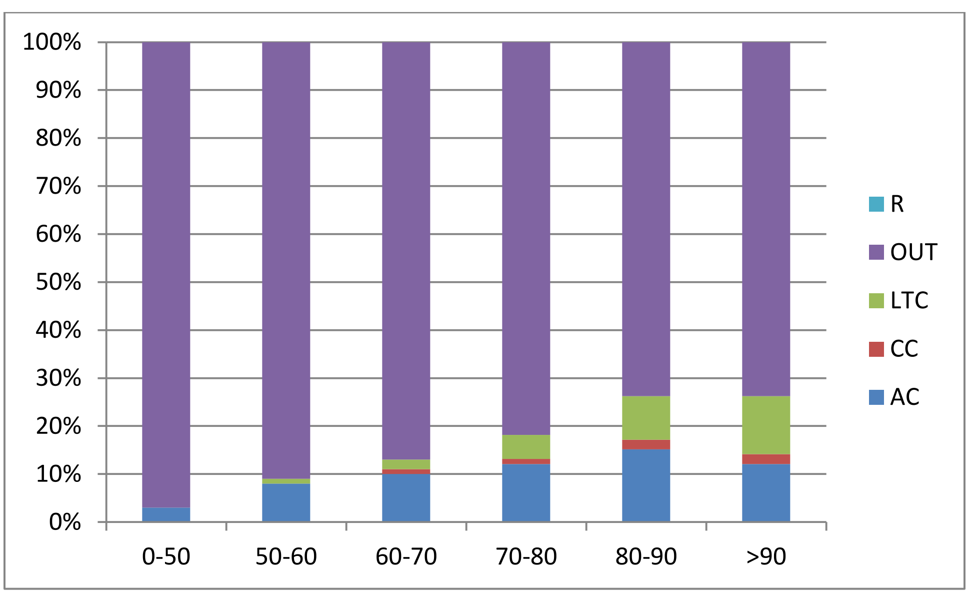


Figure 22. Flow Probability Out of Home Care to Other Nodes, Male Patients

Figure 21 and Figure 22 suggest that while gender does not impact on patient behaviour regarding outflow from Home Care, elderly patients have a higher tendency to stay in the network with their primary destinations (within the network) being Acute Care and Long Term Care. Some of these visits may be for a period of time for specific care followed by a return to Home Care.

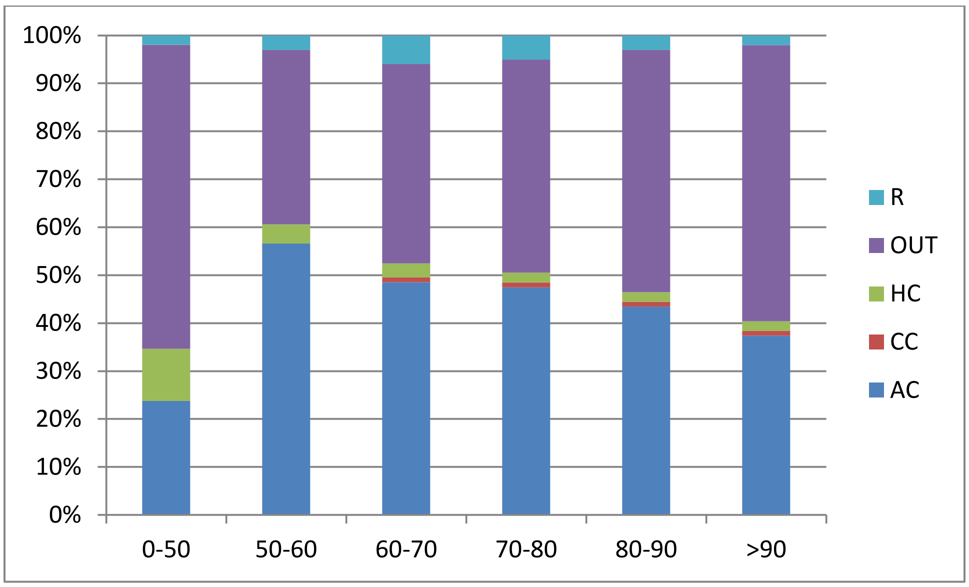


Figure 23. Flow Probability Out of Long Term Care to Other Nodes, Female Patients

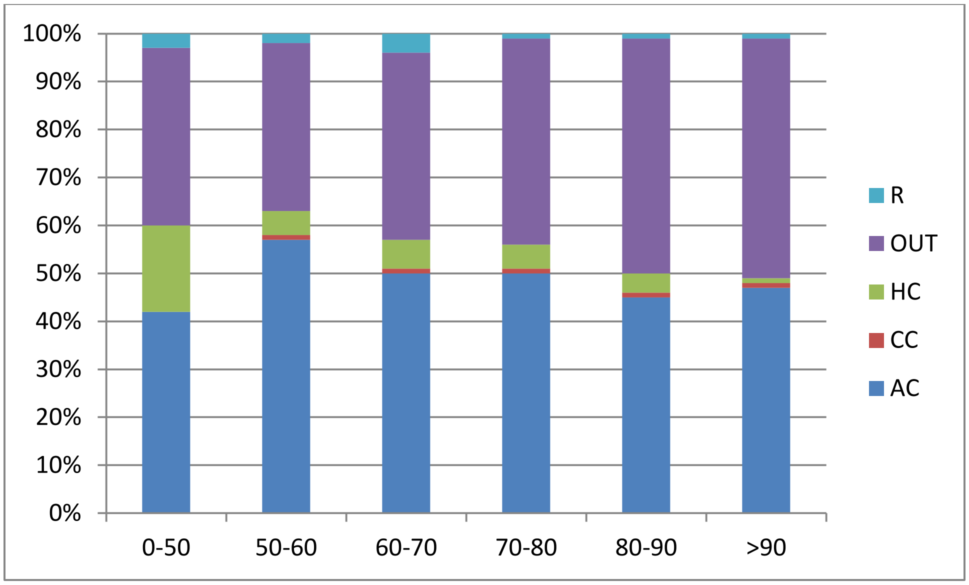


Figure 24. Flow Probability Out of Long Term Care to Other Nodes, Male Patients

Figure 23 and Figure 24 depict the difference in behaviour regarding outflow from LTC for female and male patients. For example, while a high percentage of patients (50% on average) go to Acute Care, it has more fluctuations for female patients (From 25% for those with age less than 50 to 55% for those in their 50s). In addition, a larger proportion of male patients transfer to Home Care.

LOS Analyses

Another CCN parameter that we need as simulation input is the Length of Stay (LOS) in each node for each age-gender cohort. Derived LOS distributions fit an exponential distribution with a chi square goodness of fit test with very small p-value (<0.005).

LOS analyses for each age cohort for female and male patients are given in Table 9 and Table 10.

Table 9. LOS Analyses for Female Patients

Node	AC	CC	LTC	HC	R

Age	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
0-50	3.25	6.51	521.28	730	840.75	890	200.28	487	35.8	34.3
50-60	5.55	7.96	230.87	656	449.51	883	204.98	472	24.9	22.1
60-70	6.58	10.5	134.88	420	450.50	961	226.62	414	23.5	18.8
70-80	7.31	9.24	120.41	474	728.9	902	276.56	432	21.4	18.1
80-90	8.28	8.9	112.23	300	662.1	872	361.30	42	23.2	23.2
> 90	8.17	7.91	85.28	244	461.44	621	370.18	430	22.7	11.7

Table 10. LOS Analyses for Male Patients

Node / Age	AC		CC		LTC		HC		R	
	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
0-50	4.22	8.84	349.93	781	680.11	768	218.33	472	41.4	30.3
50-60	6.14	10.2	209.53	707	345.72	759	176.01	430	30.2	27.1
60-70	6.57	9.37	84.14	153	523.36	734	204.13	418	28.2	26.8
70-80	7.42	10.1	84.71	10.1	443.05	732	250.64	423	24.5	18.3
80-90	8.24	9.97	72.21	124	395.09	579	288.34	371	23	14.9
> 90	8.2	7.94	60.85	81.9	299.08	411	280.35	343	22.6	15.2

As shown in Table 9 and Table 10 the mean LOS in Acute Care increases for older patients. It is worth noting that this refers only to the acute phase of their LOS and not the time they spend in the hospital as ALC. This number is slightly lower for female patients. In Rehab, there is a negative correlation between age and LOS with a decrease from 40 to 22 for male patients and 32 to 22 for females. The same trend is seen for LOS in Chronic Care. Evidently, LOS in Home Care increases with the increase in age.

Life Span

It is well known that patients often stay in some services more than the required LOS because of long waiting times for the next destination. While, in the data sets, this additional stay is separated out in acute care, this is not done for the other nodes in the network. In a highly congested system it is likely that many patients will die while waiting for service at another node. To address this issue we considered a discrete probability of staying in the entire system for a specific period of time for each class of patient as depicted in Table 11 and Table 12.

Probabilities are derived from frequency of death of Canadians at each age[9]. These probabilities are used to determine whether a patient waiting for transfer to another node may in fact die while waiting and thus exit the network.

Table 11. Probability of Staying in the System for X Years for Each Class of Patient in %, Female Patients

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	>13
0-50	0.11	0.11	0.12	0.13	0.14	0.15	0.16	0.18	0.20	0.21	0.23	0.24	0.26	0.28	97.49
50-60	0.71	0.74	0.79	0.83	0.88	0.94	0.99	1.04	1.09	1.14	1.19	1.26	1.31	1.37	85.71
60-70	1.31	1.39	1.45	1.52	1.58	1.64	1.71	1.81	1.91	2.05	2.19	2.36	2.53	2.72	73.84
70-80	2.65	2.85	3.05	3.29	3.53	3.77	4.05	4.30	4.55	4.79	5.01	5.15	5.26	5.20	42.56
80-90	8.38	8.58	8.71	8.52	8.25	7.90	7.46	6.94	6.31	5.60	4.85	4.11	3.38	2.78	8.24
>90	35.87	22.81	14.25	9.15	6.04	4.09	2.75	1.83	1.21	0.78	0.50	0.31	0.18	0.11	0.12

[9] http://www.statcan.gc.ca/pub/91-209-x/2013001/article/11867/fig/desc/desc03-eng.htm

Table 12. Probability of Staying in the System for X years for Each Class of Patients in %, Male Patients

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	>13
0-50		0.18	0.20	0.21	0.23	0.25	0.27	0.29	0.32	0.34	0.37	0.40	0.43	0.46	95.87
50-60	1.12	1.20	1.28	1.36	1.45	1.54	1.62	1.69	1.76	1.84	1.91	1.97	2.04	2.11	77.11
60-70	2.26	2.33	2.40	2.49	2.56	2.63	2.73	2.83	2.95	3.06	3.23	3.38	3.54	3.70	59.92
70-80	4.44	4.65	4.88	5.09	5.26	5.43	5.57	5.66	5.71	5.69	5.56	5.39	5.13	4.78	26.78
80-90	12.50	12.00	11.29	10.33	9.32	8.27	7.21	6.22	5.22	4.29	3.45	2.70	2.06	1.56	3.59
>90	39.97	24.91	13.85	8.10	5.05	3.17	2.00	1.23	0.74	0.44	0.25	0.13	0.07	0.04	0.04

Model Description:

As discussed earlier, queuing models present in the literature review are limited as they cannot provide transient behaviour in order to determine the impact of gradual changes in capacity and/or demand. The queuing model of Noghani et al. [6] does not account for transient behaviour of the CCN, does not allow for multiple patient types and provides only steady state results assuming a fixed demand distribution over many years.

We build on the conceptual model of the network by providing a simulation model for a more realistic setting that allows for year by year capacity plans and transient behaviour in terms of demand and patient flow. Moreover, patient classification based on age and gender is incorporated in the model.. We are using this simulation model to test the robustness of the the queuing network model's capacity plans to a more realistic description of patient flow and LOS based on patient cohorts and the graduated capacity increase taking into account the transient behaviour of the system and the expected increase in demand.

The CCN which we build our model on is depicted in Figure 25. All the nodes and their definitions can be found in the introduction.. Entries to the system are through Acute Care and Home Care (the only two nodes with significant arrival rates from outside the network).

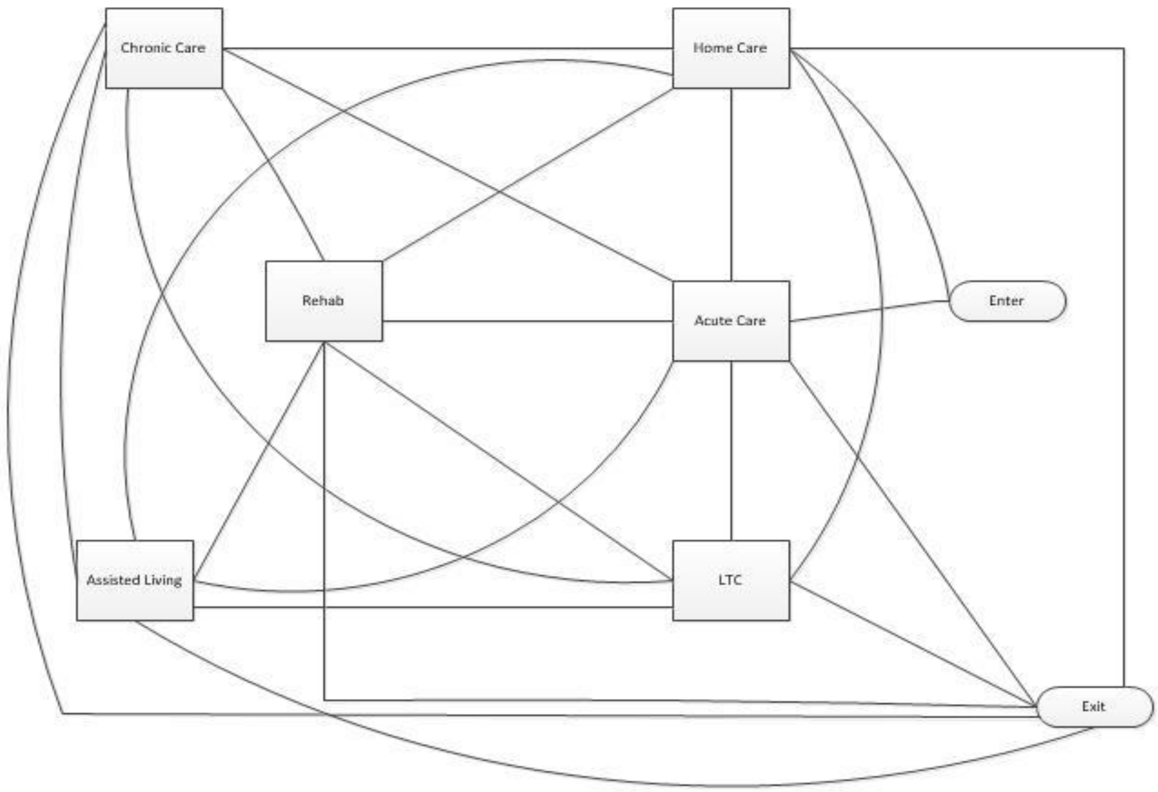


Figure 25. Community Care Network

Simulation Logic:

As mentioned earlier, there are six nodes in the network each representing a service type. Arrivals (new patients) occur with the mean and distributions determined from the historical data and broken down into cohorts based on age and gender. The patient remains in service for an amount of time generated by a distribution specific to their cohort and will transfer to the next node with the probability of transfer also specific to the cohort. If there are beds available in the next node, the patient will leave the current node and release the bed otherwise the patient will remain on the waitlist until a bed in the appropriate facility becomes available and only then release the bed for the current node. This reflects the reality that it is not possible to simply discharge a patient without services to wait at home until the appropriate services become available. This movement continues until the patient is discharged from the network either due to recovery or death. The simulation logic is elaborated below:

1. Patient Generation

New patients arrive to the system from two main entry nodes: Acute Care and Home Care. Each node arrival has a pattern which was depicted in **Data analyses**.

Arrival analysis

The change in arrival rates are based on demographic data provided by the Champlain LHIN. To illustrate, if the Poisson parameter for the arrival rate of a given age-gender cohort is λ, each year it will be multiplied by the rate $N(t)$ representing the rate of increase in the arrival rate in year t [12]. In this model, we considered external demand to Acute Care and Home Care as the only ones with significant arrivals from outside the network. (Demand for other nodes generally comes through either Home Care or Acute Care first.)

Life Span

The probability of staying in the system for x years, $(0 \leq x \leq 10)$ is also assigned to the new patients to the network.

Preloading existing patients

Because at the starting year of planning there are patients in different nodes, it is necessary to preload them.

2. Service Usage

The patient will remain in a service for a randomly assigned LOS specific to that class and will go to the next node with the probability of transfer for that specific cohort. LOS distributions are estimated from the historical data of clients who have exited the node. In the model, LOS will be assigned to patients probabilistically based on these distributions. Parameters of the distributions vary for each class.

3. Waitlist:

Patients discharged from a node are added to the waitlist of the next node. If there are beds available in the next node, the patient leaves the current node and releases the bed otherwise the patient remains in his/her current location until a bed in the appropriate facility becomes available. Since we only had data regarding patients in care not on the waitlist, we have a year warm up period as well in order to develop an initial waitlist. The average number in the queue for each node is the performance measure of interest. This movement continues until the patient is discharged from the CCN due to recovery or death.

4. Annual updates:

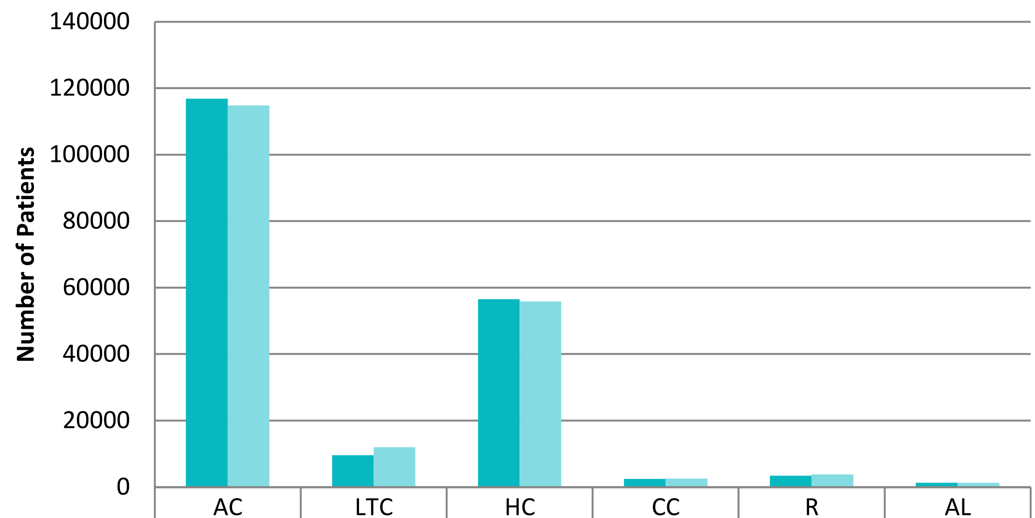
At the end of each year, arrival rates and available capacity are updated based on user input.

Model Validation:

Data for years 2013 and 2014 was used as the training data and the results of the analyses were used as the input for the model. Results of the model are compared to the result of data analyses for year 2014. Since we do not have waitlist data in order to compare model and data, we considered number of transfers between nodes as the measure of accuracy. Therefore, we recorded patient transfers between nodes and compared those to data analyses results for year 2014.

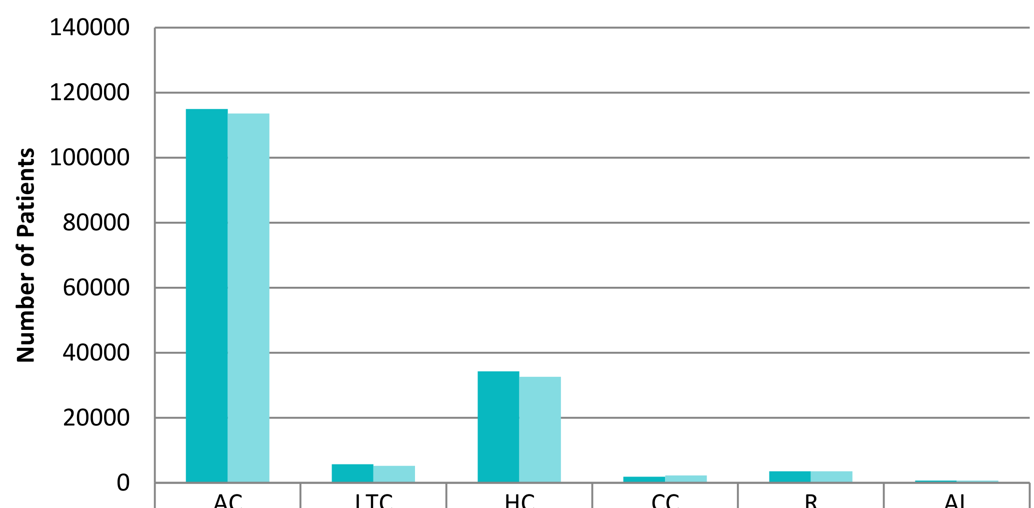
Figure 26 and Figure 27 compare the number of patients entering and exiting each node for 2014 between the data and the model. In this section initial population by the start of year

2014 is used for model initiation. It is clear that the simulation quite closely mimics the rate at which patients are transferred in and out of each service node.



	AC	LTC	HC	CC	R	AL
Data	116820	9606	56547	2414	3404	1303
Model	114789	12018	55810	2532	3812	1303

Figure 26. Entries to Each Node in Year 2014



	AC	LTC	HC	CC	R	AL
Data	114936	5726	34290	1849	3562	686
Model	113526	5254	32587	2247	3582	686

Figure 27. Exits From Each Node in Year 2014

Simulation Results and discussion:

The first results address blocking for different nodes and service usage for a ten year planning horizon. Then we illustrate how the model can be used to assess the impact of gradual increases in capacity as well as changes in expected demand. Ten replications each ten years in length and with a warmup period of one year were run for each scenario.

Base Scenario

In the base scenario, all inputs of the model are as discussed before. We use current capacity during the ten years as depicted in Table 13. Thus the results provide the blocking probability and the number of blocked patients in ten years if we continue with the current demand pattern and current capacity.

Table 13. Current Capacity of CCN nodes

Node	AC	CC	HC	LTC	R	AL
Number of Beds	2400	540	18000	7595	222	617

The average number of blocked patients at each stage as well as the blocking probability is provided in Table 14 and Table 15. Blocking occurs when the number of busy beds is equal to the scheduled number of beds and therefore the node is full (blocked). Blocking probability is the frequency of this event during ten years.

Table 14. Blocking Probability in Each Node, Base Scenario

Node	Acute care	Assisted Living	Chronic Care	Home Care	Long Term Care	Rehab
Blocking Probability	100%	33%	99%	100%	73%	74%

Table 15. Average Number of Blocked Patients at each Stage, Base Scenario

# of Blocked Patients\Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Acute Care	-	0	18	1139	22	3
Assisted Living	98	-	0	0	16	0
Chronic Care	148	0	-	62	3	2
Home Care	2883	0	187	-	116	16
Long Term Care	1904	0	19	116	-	17
Rehab	51	0	1	48	0	-
Total	5084	0	225	1365	157	-

Moreover, within ten years, on average almost all nodes are full except Long Term Care 89%, Rehab 97% and Assisted Living 78%. That the situation in reality is less dire than this is largely due to patients reneging from the wait lists and seeking private options for such things as long term care.

The results of the base scenario demonstrate that the current facility allocation is not adequate for even the current demand. In the following we use our model to determine if certain increases in facility allocation provided by Bidhandi et al can lead to decreased waiting for each node.

First Scenario: Change in Capacity

Case1: Prompt Changes in Capacity

The first proposed scenario is to increase capacity. The impact of increasing capacity on performance measures is analyzed through two different approaches. In the first case, we assume that the additional capacity is available from the outset. This allows us to see whether, in the long run, this capacity boost would be sufficient and thus to confirm the results of the queuing model which is based on long run averages. Thus the simulation is run with the new capacity for the full 10 year planning horizon. The new capacity values are based on a queuing theory model from the research done by Noghani et al.[6], overlaid with a simulated annealing approach to determine optimal capacity that minimizes the cost subject to a constraint on the sum of the blocking probabilities (work forthcoming by Bidhandi, Noghani and Patrick). We use the simulation model to determine whether the capacity plan suggested by the simulated annealing approach works as well in the more reaslistic setting of the simulation. Table 16 shows the change in the number of beds. In this case, during the warmup period, capacities remain the same as in the base scenario to generate current waitlists and they will change to the amount illustrated in Table 16 after the warm-up. Based on the queuing network model it would appear that community care is severely under capacitated while acute care could in fact be reduced in size.

Table 16. New Capacities in Each Node, First Scenario, First Case

	AC	CC	LTC	HC	R	AL
Number of beds with blocking threshold at 0%	1820	863	14056	24901	313	1315
Changes Compared to Base Scenario in %	-24%	60%	38%	85%	41%	113%

Table 17 presents the blocking probabilities and Table 18 the average number of blocked patients for the setting with the sum of the blocking probabilities constrainted to be zero.

Table 17. Blocking Probability in Each Node, First Scenario, First Case

Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Blocking Probability	1%	0%	0%	0%	0%	0%

Table 18. Average Number of Blocked Patients at each Stage, First Scenario, First Case

# of Blocked Patients\Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Acute Care	-	0	0	0	0	0
Assisted Living	0	-	0	0	0	0
Chronic Care	0	0	-	0	0	0
Home Care	2	0	0	-	0	0
Long Term Care	2	0	0	0	-	0
Rehab	0	0	0	0	0	-
Total	4	0	0	0	0	0

The simulation model confirms that with the optimal capacities the blocking probbailities are equal to zero for almost all of the nodes. In the next case, we predict the behaviour of the system where the optimal number of beds is built up gradually.

Case 2: Gradual Changes in Capacity

To be more realistic, the optimal number of beds cannot be provided immediately. Hence, in the second case; the optimal capacity is built up during ten years. We do not reduce the acute care capacity as that capacity is essential until the capacity at the other nodes has been sufficiently ramped up. The annual changes during these ten years are shown in Table 19.

Table 19. Annual Increment in Capacity of Each Node, First Scenario, Second Case

Node	AC	CC	HC	LTC	R	AL
Increase per year	0	36	767	718	10	78

Results of the model for the ten year planning horizon are depicted in Table 20 and Table 21.

Table 20. Blocking Probability in Each Node, First Scenario, Second Case

Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Blocking Probability	99%%	0%	58%	90%	7%	47%

Table 21. Average Number of Blocked Patients at each Stage, First Scenario, Second Case

# of Blocked Patients\Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Acute Care	-	0	32	1051	4	30
Assisted Living	104	-	0	0	1	0
Chronic Care	183	0	-	47	0	5
Home Care	3090	0	123	-	6	21
Long Term Care	2122	0	12	79	-	23
Rehab	75	0	1	35	0	-
Total	5574	0	168	1212	11	79

Having blocked nodes under scrutiny, we can find bottlenecks of the network which are transfers to Acute Care and Home Care. The reason may be due to keeping Acute Care capacity as before while other nodes are serving more patients. So the flow will be smoother in other nodes which leads to higher demand from the network especially for Home Care and Long Term Care over the ten years.

Second Scenario: Increasing Demand and Capacity

In this Scenario, demand and capacity both grow. Demand grows year by year according to demand forecasted in Table 23 and capacity is increased to the optimal number of beds depicted in Table 16 - first for the whole planning horizon and second gradullay as mentioned in the second case of the first scenario. Note however that the recommended number of beds is based on a queuing model with inputs based on the current demand and not forecasted future demand. The intent here is simply to demonstrate the ability of the simulation model to provide an analysis of the impact of increasing demand on the performance metrics based on a given capacity plan.

As explained in the introduction, in reality, demand for community care facilities are increasing mainly due to increases in the seniors' population. LHIN experts provided us with the future forecast of the Champlain wide population. We used these forecasts to find the population growth rates to update the mean daily demand for the entry points - Acute Care and Home Care. The demand growth rate with respect to year 2015 and its impact on demand is shown in Table 22 and Table 23 respectively. Mean of the arrival distribution in each year is derived by adding the mean arrival in year 2015(λ) by the growth rates($N_{(t)}$) for year "t" times λ. Growth rates($N_{(t)}$) are provided in Table 23.

Table 22. Population Growth Rate with Respect to Year 2015, Champlain Wide

Year	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
Population growth rate	1.1%	2.3%	3.5%	4.7%	6.0%	7.2%	8.5%	9.8%	11.1%	12.4%	13.7%

Table 23. Updated Mean of Arrivals per Day for Entry Nodes for Years 2016 to 2026

	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
HC	45.8994	46.4442	46.989	47.5338	48.124	48.6688	49.259	49.8492	50.4394	51.0296	51.6198
AC	272.4645	275.6985	278.9325	282.1665	285.67	288.904	292.4075	295.911	299.4145	302.918	306.4215

Case1: Prompt Changes in Capacity

Again in this scenario, the mean arrival rate and capacity is kept at the current values for the warmup period. Then demand will increase year by year. The blocking probability at each stage is depicted in Table 24 and the average number of blocked patients at each stage is depicted in

Table 25.

Table 24. Blocking Probability in Each Node, Second Scenario, First Case

Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Blocking Probability	7%	0%	0%	12%	0%	0%

Table 25. Average Number of Blocked Patients at each Stage, Second Scenario, First Case

# of Blocked Patients\Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Acute Care	-	0	0	0	0	0
Assisted Living	0	-	0	0	0	0
Chronic Care	0	0	-	0	0	0
Home Care	2	0	0	-	0	0
Long Term Care	2	0	0	0	0	0
Rehab	0	0	0	0	0	-
Total	4	0	0	0	0	0

The tables above depicts that the optimal numbers of beds for the current population can meet the future demand if the required number of beds are provided from the outset.

Case 2: Gradual Changes in Capacity

In this case, the capacity is built up year by year as in the second case of the first scenario. The results are depicted in Table 26 and Table 27.

Table 26. Blocking Probability in Each Node, Second Scenario, Second Case

Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Blocking Probability	99%	0%	56%	93%	7%	45%

Table 27. Average Number of Blocked Patients at each Stage, Second Scenario, Second Case

# of Blocked Patients\Node	Acute care	Assisted Living	Chronic care	Home Care	Long Term Care	Rehab
Acute Care	-	0	32	1096	3	19
Assisted Living	106	-	0	0	1	0
Chronic Care	184	0	-	48	0	4
Home Care	3111	0	127	-	5	16
Long Term Care	2113	0	13	82	0	19
Rehab	72	0	1	37	0	-
Total	5586	0	173	1263	9	58

As expected, the waitlist size in the second case is more than the first case of this scenario. Compared to the second case of the first scenario, we have a little increase in the waitlist size. So, for example for Acute Care it increases 0.3% and for Home Care it increases 1.1%. The comparison of results of different scenarios for the same case shows that the changes in the number of patients waiting is not that different with the anticipated increase in demand. For longer periods we cannot tell and every possible situation should be tested via the model.

Assumptions and Limitations:

While our research is more comprehensive compared to previous research done in this area, there are explicit and implicit assumptions during analyses and modeling that it is good to bear in mind. The main ones are listed below.

- In our model, the queue is first come, first served and patients will take their first choice, although we know CCAC has regulations over patient preferences and priorities. These are unlikely to make a major difference until the wait list size is brought down to a more manageable level.
- Since we referred to optimal solutions from another model in this problem setting, we tried to be consistent over assumptions. Thus, although the CCAC suggested separating Home Care services to “Home Care Chronic” and “Home Care Other populations” we have one Home Care service .Also, as mentioned in **Data Analyses**, Long Term Care has arrivals directly from the community that we did not consider in our model inputs. This flow is small however compared to the flow into acute and home care.
- It is possible that a patient, who moves from one facility to another, may still keep the previous bed reserved. As an example, under CCAC regulations, if a patient leaves LTC for a duration of less than 30 days, he or she can keep the bed. In our model, the bed is vacated.
- The number of visits as a covariate of LOS is not considered in the model even though the data suggests that it might be for some nodes. For example in Acute Care, LOS in the second or third visit by average is slightly less than the LOS in the first visit. For simplicity this was not included.
- Since there was no distinction between LOS for care and LOS for waiting in datasets except Acute Care, the LOS of patients may be overestimated in the model.
- Assisted Living patients are not classified due to unavailability of data.

Conclusion and Further Expansions:

One important aspect of the health system design is patients' movement across the system. It is reasonable to assume that population aging directly impacts on patient flow. Compared to younger people, seniors remain in emergency departments and acute care settings for longer periods and are more likely to require community care post-discharge. Therefore, it is important to consider the issue of an aging population and its future health care demands through modelling and simulation of patient flow, incorporating forecasting models to predict arrival rate changes over long run planning horizons. Increasing demand for community health services which is mainly due to the aging phenomenon impacts on policies regarding capacity planning in the long run. The demand is from both community-mainly seniors-, and those discharged from the hospital but waiting for care elsewhere (ALC). This thesis aims to contribute to alleviating the ALC challenge by proposing a simulation method for modelling patient flow in a set of community care facilities. While earlier work had developed models that provide steady state results, through this work we were able to test the validity of the steady state results in a more realistic setting (with patient classes and cohort specific flows and LOS) than the stylized queuing network model. We demonstrated that the capacity plan from the queueing network model does indeed work well in the long run but that the transient behaviour of the system while capacity is being increased to the levels required by the queuing network model can be quite poor. While the queuing network model may call for reductions in some nodes (i.e. in acute care), implementing those reductions may in fact be detrimental to the system until the necessary capacity at others nodes has been increased. This once again highlights the importance of examining the network of care as a whole rather than each service type separately.

For future research, we recommend using a simulation optimization approach which updates parameters of the optimization consistently and periodically from simulation and vice versa. More over, while our data analyses showed age and gender impact patient behavior regarding LOS and outflow from a node, other covariates such as diagnosis and history of previous visits could be investigated through further research.

Appendix

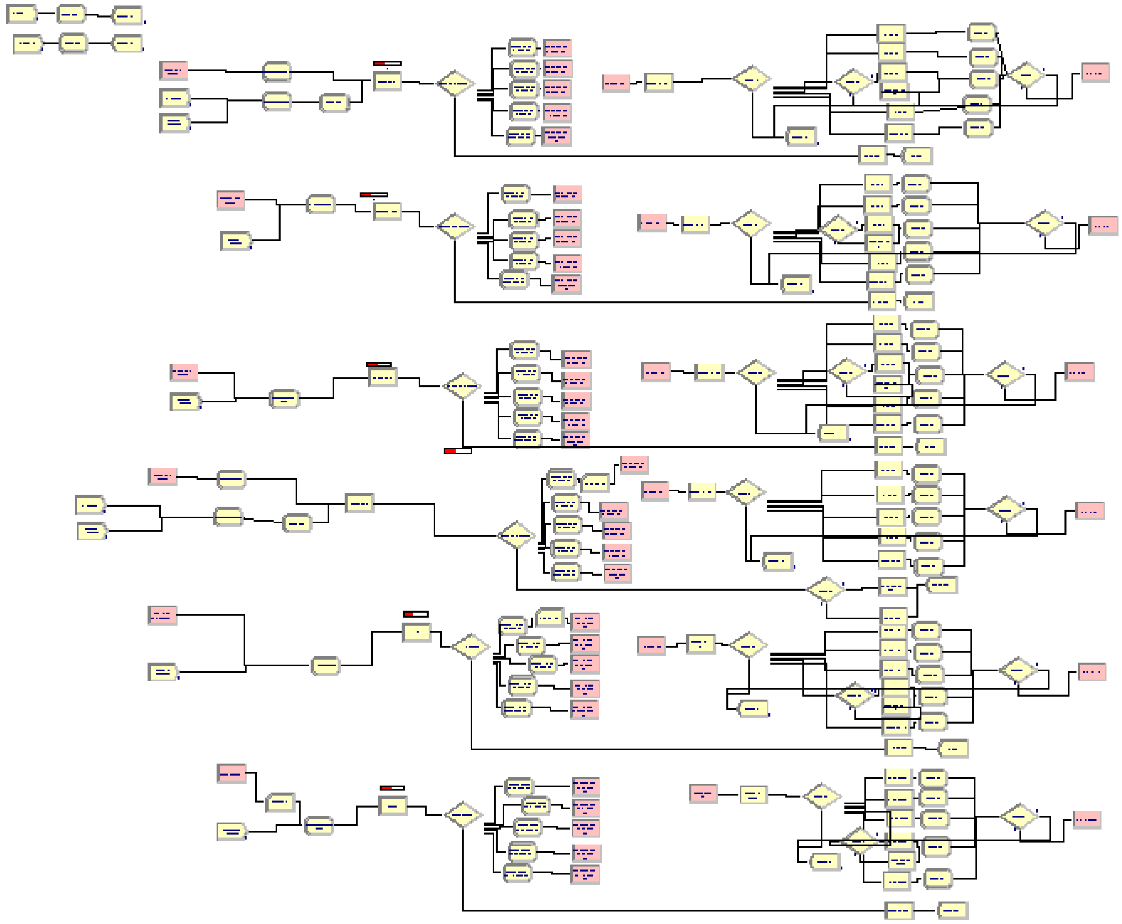


Figure 28. A Snapshot From Simulation Modules

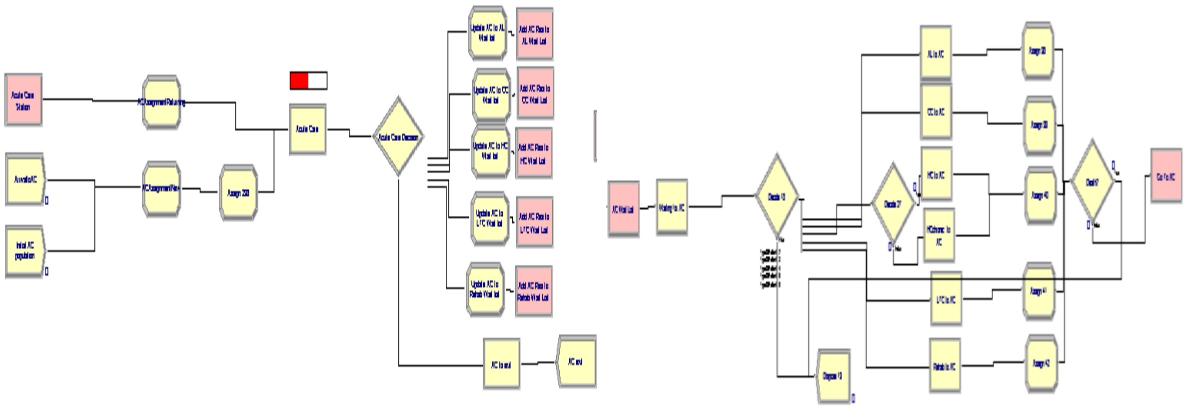


Figure 29. A Snapshot From simulation Modules

Table 28. Outflow from AC

Age at Entry	CC		HC		LTC		OUT		R	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
0-50	0%	0%	4%	6%	0%	0%	96%	93%	0%	0%
50-60	1%	1%	17%	16%	2%	2%	78%	78%	2%	2%
60-70	2%	2%	21%	18%	4%	3%	70%	74%	4%	3%
70-80	3%	3%	23%	21%	8%	5%	60%	67%	6%	4%
80-90	4%	4%	27%	25%	19%	14%	40%	50%	10%	7%
>90	5%	4%	28%	26%	30%	27%	28%	35%	10%	8%
Total	1%	1%	12%	12%	4%	3%	81%	81%	3%	2%

Table 29. Out Flow From CC

Age at Entry	AC		HC		LTC		OUT		R	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
0-50	44%	53%	4%	3%	4%	3%	42%	29%	6%	12%
50-60	30%	33%	7%	8%	9%	6%	51%	47%	2%	6%
60-70	32%	24%	8%	9%	6%	5%	48%	55%	5%	8%
70-80	21%	22%	18%	13%	13%	9%	44%	49%	5%	7%
80-90	15%	21%	20%	18%	20%	15%	39%	44%	5%	3%
>90	7%	17%	24%	21%	26%	17%	40%	42%	3%	3%
Total	21%	25%	16%	13%	15%	10%	43%	46%	5%	6%

Table 30. Outflow From Rehab

Age at Entry	AC		CC		HC		LTC		OUT	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
0-50	8%	7%	1%	0%	5%	3%	1%	0%	85%	90%
50-60	5%	8%	1%	2%	10%	6%	1%	1%	84%	84%

60-70	7%	7%	0%	1%	8%	9%	2%	2%	83%	81%
70-80	7%	12%	1%	1%	13%	15%	2%	2%	77%	71%
80-90	8%	9%	1%	2%	16%	17%	2%	1%	72%	71%
>90	10%	9%	1%	1%	18%	13%	2%	1%	70%	75%
Total	8%	9%	1%	1%	14%	13%	2%	1%	76%	75%

Table 31. Outflow From HC

Age at Entry	**AC**		**CC**		**LTC**		**OUT**		**R**	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**
0-50	4%	3%	0%	0%	0%	0%	96%	97%	0%	0%
50-60	7%	8%	1%	0%	1%	1%	91%	91%	0%	0%
60-70	9%	10%	1%	1%	2%	2%	88%	87%	0%	0%
70-80	11%	12%	2%	1%	6%	5%	81%	81%	0%	0%
80-90	15%	15%	2%	2%	11%	9%	72%	73%	1%	0%
>90	15%	12%	2%	2%	13%	12%	70%	73%	0%	0%

Total	11%	10%	1%	1%	6%	4 %	82%	84%	0%	0%

Table 32. Outflow From LTC

Age at Entry	AC		CC		HC		OUT		R	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**
0-50	24%	42%	0%	0%	11%	18%	64%	37%	2%	3%
50-60	56%	57%	0%	1%	4%	5%	36%	35%	3%	2%
60-70	49%	50%	1%	1%	3%	6%	42%	39%	6%	4%
70-80	47%	50%	1%	1%	2%	5%	44%	43%	5%	1%
80-90	43%	45%	1%	1%	2%	4%	50%	49%	3%	1%
>90	37%	47%	1%	1%	2%	1%	57%	50%	2%	1%
Total	43%	48%	1%	1%	3%	4%	50%	46%	3%	1%

Figure 30. Survival analysis of LOS in long term care

Means and Medians for Survival Time

	Mean[a]				Median			
			95% Confidence Interval				95% Confidence Interval	
Sex	Estimate	Std. Error	Lower Bound	Upper Bound	Estimate	Std. Error	Lower Bound	Upper Bound
F	582.060	10.673	561.141	602.979	199.000	7.446	184.407	213.593
M	399.896	10.666	378.990	420.802	128.000	5.307	117.599	138.401
O	532.750	102.661	331.535	733.965	531.000	185.000	168.400	893.600
Overall	512.267	7.786	497.007	527.528	164.000	4.502	155.176	172.824

a. Estimation is limited to the largest survival time if it is censored.

References:

1. Health Canada in Collaboration with the Interdepartmental Committee on Aging and Senior Issues, Canada`s Aging Population (Ottawa, Public Works and Government Services, Canada, 2002), p.3

2. Ministry of Health and Long-Term Care, “Discharge of Hospital Patients”, Chapter 3, section 2

3. Annual Report of the Office of the Auditor Generals of Ontario (2010), Chapter3, Section 3.02

4. Appropriate level of care: a patient flow, system integration and capacity solution Report by the expert panel on alternate level of care (December 2006)

5. Inpatient Discharges Data, Ontario MOHLTC, Provincial Health Planning Database (PHPDB) 2005, 2006

6. Pedram Noghani Ardestani(2014),” Modeling Community Care Services for Alternative level of Care (ALC) Patients: A Queuing Network Approach”

7.CBC news, posted Sep 29th, 2015

8. Feng Lin, Nan Kong & Mark Lawly (2011), Chapter 12, “Capacity Planning for publicly funded community based LTC services”, Community Based Operation Research, Volume 167, pp 297-315

9. Harper& Shahani AK (2002), “Modelling for the planning and management of bed capacities in hospitals”, Journal of Operation Research Society53 (1):11-18

10. Jonathan Patrick, K.Nelson & Dan Lane(2015) , “A Simulation Model for Capacity Planning in Community Care “, Journal of simulation,9,pp:111-120

11. N. Koizumi, E. Kuno & T.E. Smith(Feb.2205), “Modeling patient Flows Using a queuing Network with Blocking”, Health care management science, vol.8, no.1, pp:49-60

12. Jonathan Patrick (2011): “Long Term Care: the Real Case of Hospital Congestion?” Production and Operation Management, 20(3):347-358

13. Hare, W. L., A.Alimadad, H.Dodd, R.Fergusan (2009), “A deterministic model of home care and community care patient’s counts in British Columbia.” Health Care Management Sci.12 (1) 80-98

14. K.M. Bretthauer, H.S. Heese, H. Pun, and E. Coe (2011)“Blocking in Health Care Operations: A New Heuristic and Application,” Production and Operations Management, Vol.20, no.3, pp.375-391

15. Zhang et al. (2012) “A simulation optimization approach to long-term care capacity planning”, Operations Research, Volume 60, issue 2, pp.249-261

16. J. B. Jun et al. (1999),” Applications of Discrete event simulation in Health Care Clinics: A survey”, The Journal of the Operational Research Society, Vol. 50, No.2, pp.109-123

17. Bozena Mielczarek and Justyna Uzialko-Mydlikowska (2010), “Application of computer simulation modeling in the health care sector: a survey” Journal of simulation: Transactions for the society for Modeling and Simulation International: 88(2) 197-216

18. peter T.VanBerkel and John T.Blake(2007), “A comprehensive simulation for wait time reduction and capacity planning applied in general surgery”, Health Care Managemenr Sciense, Volume 10, Issue 4, PP 373-385